On PAPR Reduction of OFDM using Partial Transmit Sequence with Intelligent Optimization Algorithms

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This is to certify that the work presented in the thesis entitled *On PAPR reduction of OFDM using Partial Transmit Sequence with Intelligent Optimization Algorithms* submitted by *Mangal Singh*, Roll Number 510EC804, is a record of original research carried out by him under my supervision and guidance in partial fulfillment of the requirements of the degree of *Doctor of Philosophy* in *Electronics and Communication Engineering*. Neither this thesis nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

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Dedicated to my family without whom none of my success would be possible.

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Abstract

In recent time, the demand for multimedia data services over wireless links has grown up rapidly. Orthogonal Frequency Division Multiplexing (OFDM) forms the basis for all 3G and beyond wireless communication standards due to its efficient frequency utilization permitting near ideal data rate and ubiquitous coverage with high mobility. OFDM signals are prone to high peak-to-average-power ratio (PAPR). Unfortunately, the high PAPR inherent to OFDM signal envelopes occasionally drives high power amplifiers (HPAs) to operate in the nonlinear region of their characteristic leading out-of-band radiation, reduction in efficiency of communication system etc. A plethora of research has been devoted to reducing the performance degradation due to the PAPR problem inherent to OFDM systems. Advanced techniques such as partial transmit sequences (PTS) and selected mapping (SLM) have been considered most promising for PAPR reduction. Such techniques are seen to be efficient for distortion-less signal processing but suffer from computational complexity and often requires transmission of extra information in terms of several side information (SI) bits leading to loss in effective data rate.

This thesis investigates the PAPR problem using Partial Transmit Sequence (PTS) scheme, where optimization is achieved with evolutionary bio-inspired metaheuristic stochastic algorithms. The phase factor optimization in PTS is used for PAPR reduction. At first, swarm intelligence based Firefly PTS (FF-PTS) algorithm is proposed which delivers improved PAPR performance with reduced searching complexity. Following this, Cuckoo Search based PTS (CS-PTS) technique is presented, which offers good PAPR performance in terms of solution quality and convergence speed. Lastly, Improved Harmony Search based PTS (IHS-PTS) is introduced, which provides improved PAPR. The algorithm has sim-

ple structure with a very few parameters for larger PTS sub-blocks. The PAPR performance of the proposed technique with different parameters is also verified through extensive computer simulations. Furthermore, complexity analysis of algorithms demonstrates that the proposed schemes offer significant complexity reduction when compared to standard PAPR reduction techniques. Findings have been validated through extensive simulation tests.

Contents

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List of Abbreviations

3GPP	3rd Generation Partnership Project
4G	Fourth Generation
ABC	Artificial Bee Colony
ACE	Active Constellation Extension
ADC	Analog to Digital Converters
ADSL	Asymmetric Digital Subscriber Lines
AWGN	Additive White Gaussian Noise
BER	Bit Error Rate
BO	Back-Off
BWAS	Broadband Wireless Access System
CCD	Complementary Cumulative Distribution
CCDF	Complementary Cumulative Distribution Function
CDMA	Code Division Multiple Access
CE	Cross Entropy
CP	Cyclic Prefix
CS	Cuckoo Search
DAB	Digital Audio Broadcasting
DAC	Digital-to-Analog Converter
DFT	Discrete Fourier Transform
DVB	Digital Video Broadcasting
EA	Evolutionary Algorithm
EM	Electromagnetism-like
FDM	Frequency Division Multiplexing
FDMA	Frequency Division Multiplexing Access

FF	Firefly
FFT	Fast Fourier Transform
GA	Genetic Algorithm
HDSL	High Bit Rate Digital Subscriber Lines
HPA	High Power Amplifier
HS	Harmony Search
HYPERLAN	High Performance Radio LAN
ICI	Inter-Carrier Interference
IEEE	Institute of Electrical and Electronics Engineering
IFFT	Inverse Fast Fourier Transform
IHS	Improved Harmony Search
IPTS	Iterative Partial Transmit Sequences
ISI	Inter-Symbol Interference
LTE	Long Term Evolution
MCM	Multi Carrier Modulation
MIMO	Multiple-Input Multiple-Output
M-PSK	M-ary Phase Shift Keying
M-QAM	M-ary Quadrature Amplitude Modulation
OFDM	Orthogonal Frequency Division Multiplexing
OPTS	Optimum Partial Transmit Sequence
PAPR	Peak-to-Average-Power Ratio
PN	Pseudo- Random Noise
PSO	Particle Swarm Optimization
PTS	Partial Transmit Sequences
QAM	Quadrature Amplitude Modulation
QPSK	Quadrature Phase Shift Keying
SA	Simulated Annealing

SC	Single Carrier
SCM	Single Carrier Modulation
SISO	Single-Input Single-Output
SLM	Selective Mapping
SNR	Signal to Noise Ratio
TI	Tone Injection
TR	Tone Reservation
UMTS	Universal Mobile Telecommunications System
WiMax	Worldwide Interoperability for Microwave Access
WLAN	Wireless Local Area Network

List of Symbols

N	Number of sub-carriers
M	Number of sub-blocks
L	Oversampling Factor
b	Bits per symbol
W	Phase rotation factors
d	Dimensions of fireflies
G_n	Generation/ Population
α	Randomization parameter
β	Scaling Factor
γ	Firefly Absorption coefficient
p_d	Discovery rate of alien eggs/solutions
K	No. of iterations
$\mathbf{x}$	Data Sequence
x_n	Time domain data sample of $\mathbf{x}$
$x(t)$	Continuous time domain signal
$P_r(PAPR)$	Probability of the PAPR
HMS	Harmony Memory Size
$HMCR$	Harmony Memory Consideration Rate
PAR	Pitch Adjustment Rate
bw	Bandwidth of Adjustment

CHAPTER 1

Introduction

"Prediction is very difficult, especially if it's about the future".

-Niels Bohr

Contents

1.1 Prelude

"Everyone wants to go wireless": the statement aptly describes the trend in modern wireless communications. At the end of the nineteenth century, James Clark Maxwell laid the initial foundation for electromagnetic radiation. He said, ***"the energy, by the engagement of electric and magnetic waves could be transported through materials and space at a finite velocity"***. In 1888, Maxwell's theory was supported by the experiments of Heinrich Hertz, who proved that light and electromagnetic waves traveled with the same velocity. His experiment with electromagnetic waves led to the development of wireless telegraph and the radio. Later in 1901, Guglielmo Marconi demonstrated the remarkable transatlantic equipment, transmitting the letter S (three dots in Morse code), over a distance of 1.8 miles. The efforts and inventions of such great scientists laid strong foundation of wireless communication. The initial success of wireless communications shortly began to be a reality, and further exploration was made towards todays booming area of personal wireless communication systems.

Wireless communications, by any measure, is the fastest-growing segment of the communications industry. It has become increasingly important not only for professional applications but also for many other fields in our daily routine [2]. In the evolution of wireless communication systems, approximately a ten years periodicity can be observed between consecutive system generations. Research work for the second generation mobile communication systems (GSM) started in Europe in 1980s, and the complete system was ready for market around 1990. At that time, research activities had already started for the 3rd generation (3G) mobile communication systems, which includes UMTS, IMT-2000. The transition from second generation (GSM) to the third generation (3G) systems observed around the year 2002 [3]. Compared to GSM networks, these UMTS systems provided much higher data rates, typically in the range of 64 to 384 Kbit/s, while achieving a peak data rate for low mobility or indoor applications of 2 Mbit/s. With the extension of High-Speed Packet Access (HSPA), data rates of up to 7.2 Mbit/s were available in the downlink. According to the current pace observed in the mobile communications market, trends shows that the 3G systems will not be the ultimate system solution. Consequently, general requirements for 4th generation (4G) system have been considered in the process of the Long Term Evolution (LTE) standardization.

Driven by enormous increase in mobile data traffic and flourishing user demands beyond 2020, significant research has already started for 5G, that are designed to meet new requirements, such as virtually zero latency to support tactile internet, Machine-to-Machine (M2M) and augmented reality. Continuing growth in demand for better mobile broadband experience is encouraging the industry to look ahead at new networks that can be utilized to meet future extreme capacity and performance demands. Efficient radio spectrum utilization for mobile networks is vital to meet the increased capacity and coverage demands. Mobile broadband spectrum resources are evolving, although the precise situation varies between countries and region, there is a generic pattern across the globe. Recently, the Government of India has initiated Digital India Program, which integrates the government departments and people of India with high-speed internet networks with the vision to transform country in to a digitally empowered society and knowledge economy.

Orhogonal Frequency Division Multiplexing (OFDM) technique has been adopted in 3G and beyond networks. 4G technology offers many advancements to the wireless communication market including downlink data rates well over 100 Mbps, low latency, efficient spectrum utilization and low cost implementation. OFDM technique employing multiple carriers applied in a wide-band radio channel has been chosen as an air interface for the downlink in the framework of LTE standardiza-

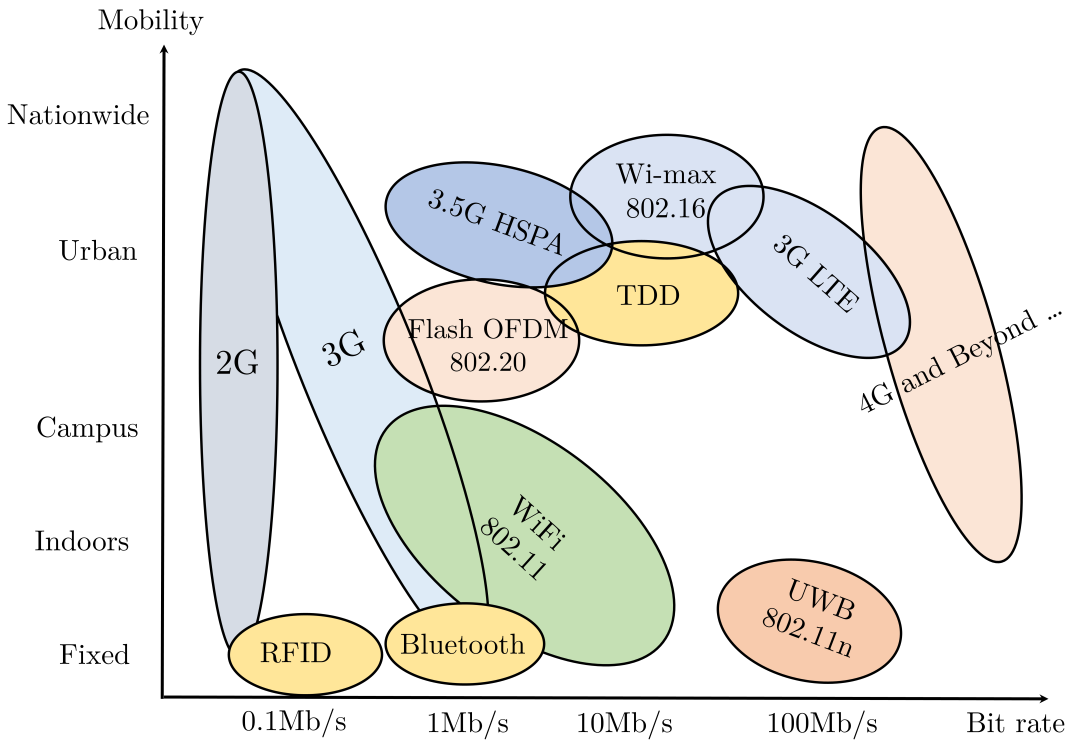


Figure 1.1: Mobility vs Bit rate for existing and future wireless communication systems

tion due to its flexibility in the technical system design. OFDM technique provides high user data rate transmission capability at a reasonable complexity and reliability [4]. Today, this transmission technique is at a completely matured stage to be applied to wideband communication systems integrated into a wireless communications environment [5]. Figure 1.1 shows the mobility vs. bit rate regions for different communication systems. Bandwidth, latency and range were always the most significant inhibitors in 3G mobile networks. Limited by download and upload speeds and slow response times, applications were stripped down to provide essential functionality. With performance similar to that of a fixed-line network and in many cases surpassing it, 4G opens the floodgates in terms of feature-rich applications from High Definition (HD) video conferencing to web-based Customer

Relationship Management (CRM) software, the wireless network no longer serves as a bottleneck to the mobile workforce.

OFDM has gained a significant presence in the wireless market place. The combination of high data capacity, high spectral efficiency, and its resilience to interference as a result of multi-path effects means that it is ideal for the high data applications that have become a major factor in today's communication scenario. Due to various advantages, OFDM was adopted for European standards to terrestrial stationary and hand-held video broadcasting systems (DVB-T, DVB-H) Digital Audio Broadcasting (DAB), wireless LAN, Wi-MAX, 3GPP, LTE, smart grid system etc. OFDM was chosen as transmission technique for 3GPP Long Term Evolution (LTE) system and 4G. OFDM systems in spite of its superior qualities are sensitive to receiver synchronization imperfections. The symbol timing synchronization error may cause Inter-block interference (IBI) and frequency synchronization error is one of the sources for Inter-carrier interference (ICI). Thus synchronization is a crucial issue in an OFDM receiver design.

The high PAPR in OFDM system is one of the biggest drawbacks.To generate the OFDM signal, sub-carriers are added up with in-phase and quadrature components. Due to this, peak power becomes greater than the average power of the OFDM signal. These peaks can cause nonlinear distortion that introduce spectral spreading, inter-modulation, and changes in the signal constellation resulting the significant reduction in power efficiency of the system. Hence, efficient methods for PAPR reduction is essential in all high-speed wireless communication systems. Besides this, reduction in PAPR is also instrumental in the removal of non-linear effect and improved efficiency of power amplifiers [1].

1.2 Modulation Schemes for High Data Rate Applications

Wireless communication systems have seen explosive growth since the last decade of 20th century with the success of Second Generation (2G) Digital Cellular Mobile services, which uses single carrier modulation systems. The Third Generation (3G) systems provided higher mobility with a reasonable data rate (up to 2 Mbps) to meet the customer's need. But, the ever increasing customer's demand has drawn the industries to search for the better solution to push data rate support up to tens and hundreds of Mbps in Fourth Generation (4G) and Fifth Generation (5G) systems. The challenge to meet the high data rate requirement meets the challenges of multipath fading, doppler effect, channel interference and intentional jamming. Hostile wireless channels have also proved to be a bottleneck for combating all the odds of wireless channels.

1.2.1 Single Carrier Modulation (SCM) Systems

In a traditional single-carrier modulation system as shown in Figure 1.2, the transmitted symbols are pulse shaped by a transmit filter and then modulated with a single carrier frequency. At the receiver, the same carrier frequency is used for demodulation, and a matched filter is employed to minimize the signal-to-noise ratio (SNR) of the received data. For digital signals, the information is in the form of bits that are modulated onto the carrier. At higher bandwidth, the duration of one bit or symbol of information becomes smaller, and hence the system becomes more susceptible to the loss of information from impulse noise, signal reflections, and other impairments. These impairments may impede the ability of receiver to recover the information sent. In addition, as the bandwidth used by a single carrier system increases, the susceptibility to interference from other continuous signal sources becomes greater.

Figure 1.2: Basic model for a Single Carrier Modulation system

In a time dispersive multipath fading wireless channel, the conventional SCM system introduces Inter Symbol Interference (ISI), which makes implementation of equalization necessary. If the data rate is low, the symbol duration is large, and if large enough as compared to the maximum delay spread of the channel, it is possible to cope with the resulting ISI without any equalization. Severe ISI limits the transmission data rate, and ISI problem is usually dealt by using complex time domain channel equalizers. The limit is given by the computational complexity of the equalizers. Moreover, achieving equalization at several Megabits per second with compact and low-cost hardware is quite difficult in practice.

1.2.2 Multi Carrier Modulation (MCM) Systems

Multi-Carrier Modulation (MCM) is an elegant technique to combat the severe ISI problem. MCM technique is used as a viable alternative to SCM, for high data rate digital transmission over channels, which exhibit high-frequency selectivity and strong multipath fading characteristics.

MCM was first used in analog military communications in 1950s. Recently, MCM has attracted attention as a means of enhancing the bandwidth of digital communications over media with physical limitations. The scheme is used in some audio broadcast services. The technology lends itself to digital television, and is used for obtaining high data speeds in Asymmetric Digital Subscriber Line (ADSL) systems. MCM is also used in Wireless Local Area Networks (WLANs).

1.2.3 Concept of MCM /OFDM

The basic concept behind the MCM technique is to divide the available spectrum into several sub-bands/ sub-channels. Each sub-band is allocated a carrier and the information is distributed among the sub-carrier/ sub-band. Each sub-carrier is modulated separately, and the ensembled data is transmitted altogether with appropriate frequency spacing. Each sub-carrier has a lower bit rate. A proper choice of the basis function allows for sub-carrier overlapping leading to higher spectral efficiency. As the number of sub-carriers increases, the spectrum shape becomes asymptotically rectangular. MCM with frequency overlapping basis function is properly called Orthogonal Frequency Division Multiplexing (OFDM) provided that orthogonality is maintained between sub-carriers. OFDM is more popular in the wireless context while in the wired environment such as DSL, the term Discrete Multi-Tone (DMT) is generally used.

Figure 1.3 shows a simplified MCM system, where the original data stream at rate R is split into N parallel sub-streams, each at rate R/N. Each sub-stream is pulse shaped and modulated with a distinct sub-carrier in the transmitter. For transmitting N sub-carriers are used and N matched filters are also used at the receiver for the demodulation of the N sub-signals. Since the symbol duration of each sub-carrier is increased by a factor of N, the ISI and the effect of multipath fading are alleviated significantly.

1.2.3.1 Advantages of MCM Systems

In the last two decades, OFDM has gained a lot of interest in diverse applications. This has been due to its favorable properties like immunity to impulse noise, uniform average spectral density, capability of handling very strong echoes coupled with advances in VLSI and signal processing techniques.

The advantages provided by MCM can be summarized as:

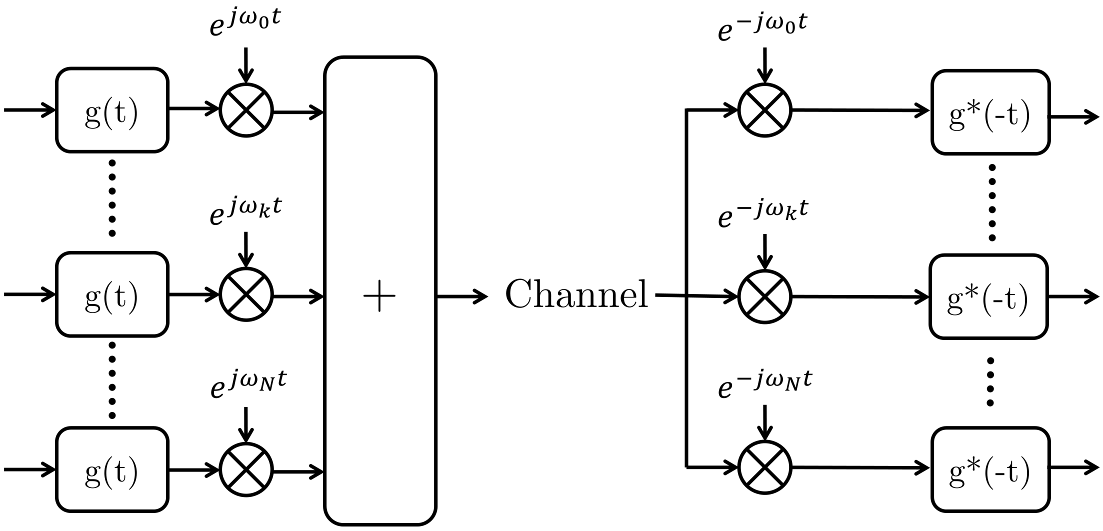


Figure 1.3: Basic model for a Multi Carrier Modulation system

- efficient and effective techniques to handle ISI
- requirement of simple equalizer
- high spectral efficiency
- flat fading per sub-carrier due to low sub-channel bandwidth.

1.2.3.2 Challenges with MCM Systems

Though MCM offers many advantages over SCM, there have been following major challenges:

- Compared to SCM systems, MCM exhibits a large Peak-to-Average Power Ratio (PAPR).
- MCM systems posses higher sensitivity to carrier frequency offset and phase error than SCM systems.
- Loss of orthogonality between sub-carriers leading to interference between sub-carriers also called ICI.

1.3 Need for PAPR reduction

Although, OFDM has proved as a powerful modulation technique for high data rate applications, it has several issues. One of the major drawbacks of OFDM system is its high Peak-to-average Power Ratio (PAPR). High PAPR is due to the nature of the signal itself, where the peak magnitude would have a significant high value whereas the average value might be quite small due to the destructive interference between many sub-carriers.

High PAPR signals are undesirable as they usually strain the analog circuitry. At the transmitter side, the High-power Amplifier (HPA) has to operate with large back-off to maintain linearity, which increases the cost. Operating power amplifiers in the non-linear region introduces signal distortion and Inter Modulation (IM) resulting in in-band interference and out-of-Band power radiation, leading to Bit Error Rate (BER) degradation and increase in Adjacent Channel Interference (ACI). In the digital domain, the data converters (A/D and D/A converters) are also required to accommodate large dynamic range of operations. To keep the quantization noise within an acceptable range in the event of large PAPR, a high precision converter is required, which increases the number of bits and hence the increased complexity of data converters.

The OFDM signal is a sum of many independent signals modulated onto subcarriers. If the phase of each signal is the same, the sum reaches the maximum, leading to high peak value. Evaluation of the variations in the envelope of OFDM signal is done using PAPR [6]. A variety of PAPR reduction schemes are used in OFDM systems, some of the popular techniques includes clipping [7], coding [8] and multiple signal representation techniques such as partial transmit sequence (PTS) [9], selected mapping (SLM) [10]. Among these techniques, PTS method has been seen to be the most promising one. PTS achieves excellent PAPR reduction capability without significant restriction on the number of sub-carriers [11].

The main purpose of this thesis is to present an analytical study of the PTS technique for PAPR reduction in the OFDM system and then to propose new scheme which provide trade-off between the improved PAPR performance and computational complexity as compared to different PAPR reduction schemes.

1.4 Motivation

The demand for higher data rate communication always provides the impetus for research in the OFDM field. One of the challenging issues of OFDM system is high PAPR. High PAPR forces the high power amplifier (HPA) to operate in the non-linear region leading to degraded power efficiency and simultaneously resulting in significant back-off power, introduction of ISI in OFDM system leading to degrade the bit error rate (BER) performance.

Numerous techniques have been proposed during the period of 10 years for reducing the PAPR. Out of them, Partial transmit Sequence (PTS) technique was the most promising one, as it gives better PAPR performance without data loss. The main issue with PTS techniques is its high computational complexity. Different optimization techniques have been applied to PAPR reduction for phase weight searches in PTS method so as to obtain the desirable PAPR reduction with a low computational complexity [12]. These includes Particle Swarm Optimization [13], Genetic Algorithm [14], Artificial Bee Colony Algorithm [15], Differential Evolution algorithm [16], Harmony Search [17] etc. The optimization techniques applied with PTS scheme have shown PAPR reduction performance for OFDM systems, since it uses all the samples of each candidate signal for peak power reduction [18].

1.5 Problem Statement

Under the backdrop of the above motivation, work done in the thesis have been broadly classified in to three objectives. They are as follows:

1. To conduct an extensive study of the techniques for PAPR reduction in OFDM systems.

    (a) Understanding the mathematical formulation and implementation of conventional Partial Transmit Sequence (PTS) technique for PAPR reduction.

    (b) Developing flexible simulation platform for analysis and performance evaluation of the PTS technique for testing applicability to OFDM systems.

2. To investigate the scope of performance improvement of PTS technique and to propose intelligent optimization techniques for PAPR reduction schemes.

3. To build up and derive improved, accurate and optimum phase weighing factor optimization algorithm, which can provide trade-off between PAPR performance and computational complexity compared to conventional PTS technique considering following issues:

    (a) Analyzing the impact of OFDM sub-carrier size, modulation order, the number of sub-blocks in PTS technique .

    (b) Evaluating performance of the optimization algorithm with respect to computational complexity.

1.6 Thesis organization

This thesis analyzes the PAPR problem in OFDM system and proposes intelligent phase factor optimization techniques for PAPR problem. The thesis is organized as follows:

The **FIRST** chapter of this thesis presents a brief introduction of the OFDM and need for PAPR reduction. The motivation and problem statement of the present research was included in this chapter. The chapter wise presentation of the thesis is also dealt here.

The **SECOND** chapter is dedicated to the high PAPR problem in general and different PAPR reduction techniques adopted in OFDM system. The definition of PAPR, its effects on systems and PAPR performance parameter are described. Following that, classifications of PAPR reduction techniques and analysis of one of the PAPR reduction method i.e. partial transmit sequence (PTS) is described. Finally literature review for PTS and different optimization algorithms with low complexity for phase factor reduction are presented.

The **THIRD** chapter analyzes the application of swarm intelligence algorithm for phase factor optimization. Here, the implementation of Firefly based PTS (FF-PTS) algorithm is done, which is seen to reduce the PAPR significantly. Simulation result shows that the proposed FF-PTS phase optimization technique can provide better PAPR reduction performance as compared to conventional IPTS scheme and at the same time works with lower computational complexity, when number of sub-blocks are large compared to IPTS technique. Also, the parameters in FF-PTS algorithm can be tuned to control the randomness as iterations proceed so that convergence can also be speed up by tuning these parameters.

The **FOURTH** chapter contributes application of a bio-inspired meta-heuristic phase optimization scheme based on Cuckoo Search (CS-PTS) algorithm. The scheme is seen to significantly reduce the PAPR of OFDM signals. The proposed scheme searches a better combination of phase vectors and offers good performance in terms of solution quality and convergence speed. Simulation results show that the CS-PTS phase optimization technique can achieve better PAPR reduction performance as compared to IPTS scheme at manageable computational complexity even when number of sub-blocks are more than the conventional PTS technique.

The **FIFTH** chapter deals with a variant of harmony search algorithm called improved harmony search based PTS algorithm (IHS-PTS) to search the optimum combination of phase factor for OFDM signals. Compared to the PAPR reduction optimization techniques like firefly algorithm, harmony search algorithm etc., the IHS-PTS algorithm provides improved PAPR due to its simple structure and very few parameters to adjust for larger PTS sub-blocks. Simulation results show that it is an efficient and feasible method with capability to provide superior PAPR performance.

Finally, the **SIXTH** chapter outlines the overall contributions of the thesis. The achievements and limitations of the work are also discussed. An analysis of further research work in the same area are also included in this chapter.

1.7 Summary

In this chapter, a brief introduction on SCM and MCM techniques are presented. This chapter also systematically outlined the motivation behind this work and the problem statement of the thesis. A concise presentation of research work carried out in each chapter has been dealt. In essence, this chapter provides an overview of the thesis in a comprehensive manner.

CHAPTER 2

PAPR for OFDM : An Overview

"When you want to know how things really work, study them when they're coming apart."

-William Gibson

Contents

2.1 Introduction

OFDM signals are characterized by high PAPR, thus necessitating the need for PAPR reduction. This is essential to control non-linear distortion, which includes in-band distortion and out-of-band radiation at High Power Amplifier (HPA). In the analog domain, high PAPR requires the RF power amplifiers to operate in high dynamic range, which leads to power inefficiency leading to low battery life in mobile devices. A high PAPR is quite undesirable in digital domain, as it requires significant word length in A/D and D/A converters to manage precision and to manage quantization noise to an acceptable level, thereby increasing the complexity of the data converters. Thus, PAPR makes the design and implementation of A/D and D/A converters, HPA and RF amplifiers increasingly more complex. These drawbacks of high PAPR may outweigh all the potential benefits offered by OFDM. Hence, it is very much essential to reduce the PAPR of the OFDM signal.

2.2 Orthogonal Frequency Division Multiplexing

Single carrier modulation techniques are vulnerable to fading and multi-path propagation, especially in the case of very high data rates. OFDM is a multi-carrier transmission technique [19] having capability to achieve high data rate transmission in a multi-path fading environment also. This feature is achieved by transmitting many narrow-band overlapping digital signals in parallel, inside single wideband channel. The concept of using parallel data transmission employing Frequency Division Multiplexing (FDM) was introduced in mid 60's [20, 21]. OFDM is an optimal version of multi-carrier transmission schemes. The idea was to use parallel data streams and FDM with overlapping sub-channels to avoid the use of complex equalization. The system also has capability of combating impulsive noise with multi-path distortion and also utilizes the available bandwidth. In telecommunication area, the terms of Discrete Multi-Tone (DMT), Multi-Channel Modulation and Multi-Carrier Modulation (MCM) are widely used and interchangeable with OFDM. In OFDM, each sub-carrier is orthogonal to all other sub-carriers. As early as 1961, a Code Division Multiplexing (CDM) scheme was proposed where sine and cosine functions were used as orthogonal signals [22]. Following which an FDM system with a Discrete Fourier Transform (DFT) was realized [23]. A complete OFDM system was proposed in 1971 [24], which included generating the signal with an IFFT and adding guard interval in the case of multipath channels. In the further development, OFDM was seen to be a efficient technique for flat and frequency selective fading channels [5, 25]. OFDM posses the property of robustness against narrowband interferences [26], since they affects only a small percentage of sub-carriers. OFDM is seen to be more sensitive to frequency and phase noise [27, 28] and it has a relatively large peak-to-average-power ratio [29].

Table 2.1: OFDM system standards

Standard	**HiperLAN/2**	**DAB**	**802.11 a/g**	**DVB-T**
No. of carriers	48 sub-carriers	1705 sub-carriers in 2k FFT	48 sub-carriers in 64 FFT	1705/ 2k FFT, 6817/ 8k FFT
Modulation Scheme	16 QAM/ 8PSK	DQPSK	64-QAM	64-QAM
Capacity	25Mbps	2Mbps	54Mbps	12-24Mbps
Bandwidth	25 MHz	1.526 MHz	20 MHz	8 MHz RF Channel
Spectral Region	5.2 Ghz	Band 3: 174-240 MHz, Band 4: 1452-1492 MHz	802.11a in 5.8 Ghz, 802.11b in 2.4 GHz	VHF/ UHF band
Technology	WLAN	Broadcasting	Wireless Technology	Broadcasting

The development of VLSI technology and digital signal processing has made the OFDM technology not only possible but made it as a major milestone in the field of wireless communications. Key features of some common OFDM based systems are presented in Table 2.1:

2.2.1 OFDM Technology

Orthogonal Frequency Division Multiplexing can be thought of as a modulating technique as well as a multiple access scheme. As a modulation scheme, it is well suited to handle adverse environmental conditions while, as a multiple access scheme, it offers high spectral efficiency and diversity.

Figure 2.1 illustrates the difference between the conventional non-overlapping multi-carrier technique and the overlapping multi-carrier modulation technique. As shown here, the overlapping multi-carrier modulation technique can provide nearly 50 percent of bandwidth reduction. While realizing the overlapping multi-carrier technique, crosstalk between sub-carriers needs to be reduced, which can be achieved by maintaining orthogonality between the individually modulated sub-carriers. The word orthogonal indicates that there is a precise mathematical relationship between the frequencies of the carriers in the system [30]. This is illustrated in Figure 2.2, which shows an example of OFDM signal spectra. With perfect synchronization at the receiver, the information on each sub-carrier can be detected without the interference from other sub-carriers.

2.2.2 OFDM Signaling

An OFDM symbol consists of N subcarriers, each separated by frequency spacing of Δf. Here, the total Bandwidth B is divided into N equally spaced sub-carriers. All the sub-carriers are orthogonal to each other within a time interval of length $T = \frac{1}{\Delta f}$. With this, subcarrier can be modulated independently with the complex modulation symbol $X_{m,n}$, where m is a time index and n is a sub-carrier index. Within the time interval T, signal of the m^{th} OFDM block period can be described

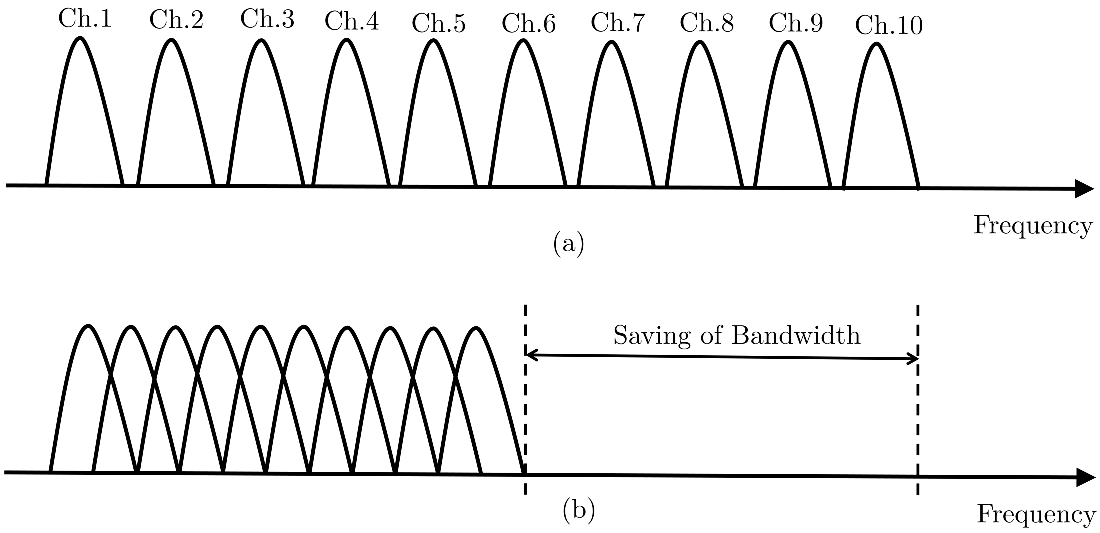


Figure 2.1: Concept of OFDM signal: (a) Conventional multi-carrier technique and, (b) orthogonal multi-carrier modulation technique

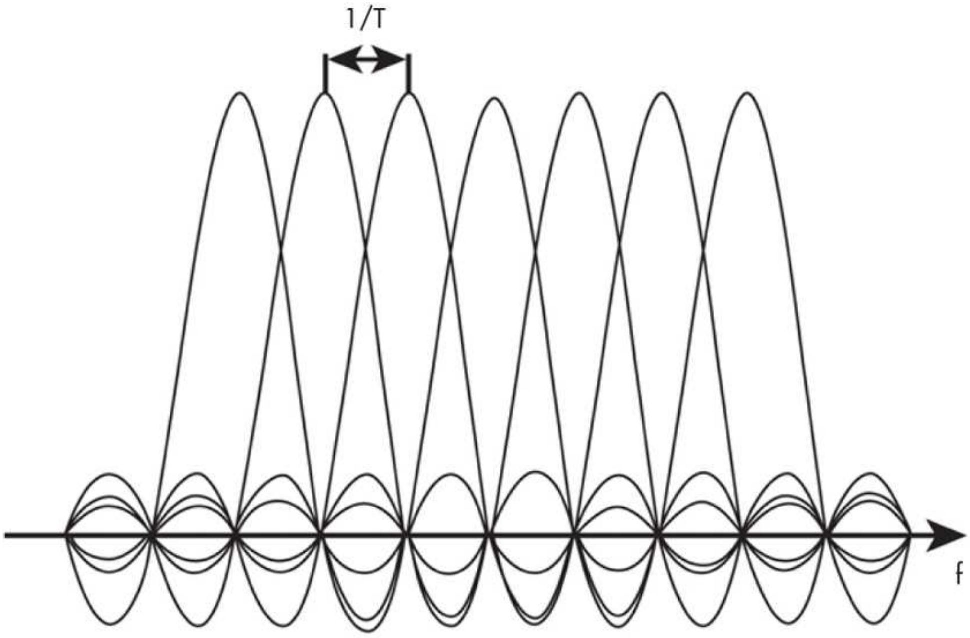


Figure 2.2: Example of an OFDM signal spectra

as

$$x_m(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_{m,n} g_n(t - mT) \tag{2.1}$$

The total continuous time signal $x(t)$ consisting of all the OFDM blocks is given by

$$x(t) = \frac{1}{\sqrt{N}} \sum_{m=0}^{\infty} \sum_{n=0}^{N-1} X_{m,n} g_n(t - mT) \tag{2.2}$$

where $x(t)$ is the time domain data sequence. Now, consider a single OFDM symbol when m=0. Without loss of generality it can be shown, because there is no overlap between different OFDM symbols, since m=0, $X_{m,n}$ can be replaced by X_n. Then the OFDM signal can be described as

$$x(t) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n e^{j2\pi n \Delta f t} \tag{2.3}$$

where X_n is the frequency domain data sequence and $e^{j2\pi n \Delta f t}$ constitute sub-carrier frequency for n=0 ... $N-1$. If the bandwidth of the OFDM signal is $B = N \times \Delta f$ and the signal $x(t)$ is sampled at sampling time $\Delta t = \frac{1}{B} = \frac{1}{N\Delta f}$, the OFDM signal is in discrete time form and can be shown as

$$x(k) = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} X_n e^{j2\pi kn/N}, k = 0, 1..., N-1 \tag{2.4}$$

where, n denotes the index in frequency domain and X_n is the complex symbol in frequency domain [31].

2.2.3 Modulation and Demodulation Procedure

The block diagram of a generic OFDM system is presented in Figure 2.3. In this figure, at the transmitter, the input bit stream is first coded by using an encoder. Following this, the coded serial bit-stream is parsed into N parallel bit streams by using the Serial-to-Parallel (S/P) converter. Each of these parallel bit streams are subsequently converted to complex data symbols X_k. An IFFT converter is then used to modulate the OFDM symbols to discrete-time OFDM signals one by one. The data symbols in each OFDM block are then modulated by the different sub-

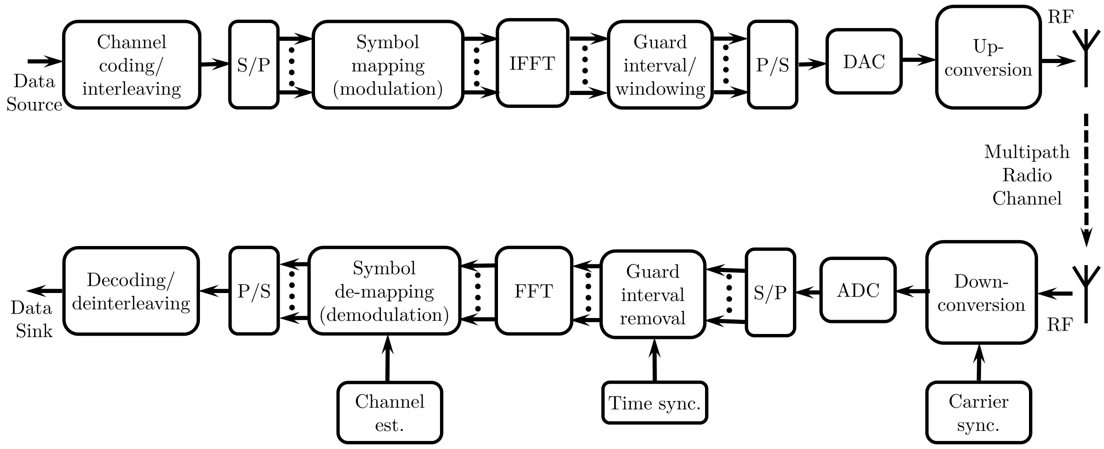


Figure 2.3: The block diagram of OFDM system [1]

carriers. After adding the cyclic prefix, the discrete-time OFDM signal is converted into a serial signal by using the Parallel-to-Serial (P/S) converter. The discrete-time signal thus obtained is then transferred into the continuous-time domain for transmission by using a Digital-to-Analog (D/A) converter. Finally, this signal is amplified by using an HPA and is up-converted to the carrier frequency to facilitate transmission in wireless channel.

At the receiver, the received analog signal is first down-converted to analog baseband signal. After the Analog-to-Digital (A/D) conversion, the obtained digital signal is parsed into parallel data symbols, and cyclic prefix is removed. The resulting data symbols are demodulated by using an FFT converter. The output symbols are then converted back to a serial bit stream by the digital demodulation and the P/S conversion. After decoding, the input bit stream is recovered at the receiver end.

2.2.4 OFDM advantages and disadvantages

After having introduced the OFDM technology in the previous section, its major advantages and disadvantages are as follows:

2.2.4.1 OFDM advantages

OFDM has been used for many high data rate wireless communication systems because of the advantages it provides. Some of these includes

- **Immunity to selective fading:** One of the main advantages of OFDM is that it is more resistant to frequency selective fading compared to single carrier systems because the signal divides the overall channel into multiple narrow-band channels, that are affected individually as flat fading subchannels.

- **Protection against Intersymbol interference:** The extended symbol time (due to lower data rate per channel) makes the signal less susceptible to affects of the channel such as multipath propagation which introduces ISI. The use of a cyclic prefix between consecutive OFDM symbols helps to eliminate ISI. It is less sensitive to sample timing offsets than the single carrier system.

- **Spectrum efficiency:** Using close-spaced overlapping sub-carriers, a significant bandwidth conservation is seen, which makes use of the available spectrum more efficiently.

- **Resilient to narrow-band effects:** Using adequate channel coding and interleaving it is possible to recover symbols lost due to the frequency selectivity of the channel and narrow-band interference.

- **Simple channel equalization:** In a single carrier system, equalization is necessary to make the channel frequency flat. But equalization amplifies noise substantially. As a result, performance of the single carrier system with low power signal is affected due to high attenuation in some bands, since all used frequencies are given equal importance during equalization process.

In OFDM systems, wide-band channels are divided into flat fading sub-channels, thus reducing the equalization complexity in the receiver. It makes it possible to use maximum likelihood decoding with reasonable complexity.

2.2.4.2 OFDM disadvantages

While OFDM has been widely used, and there are still a few disadvantages, that needs to be addressed when considering its use.

- **High Peak-to-average Power Ratio:** Presence of a vast number of sub-carriers with varying amplitude results in a high peak to average power ratio (PAPR) of the system with large dynamic range. This in turn affects the efficiency of the RF amplifier.

- **Synchronization (timing and frequency) at the receiver:** Symbol Timing Offset (STO) and Carrier Frequency Offset (CFO) effects have major impact on the performance of OFDM systems. Correct timing between FFT and IFFT is essential at the receiver side. OFDM systems are highly sensitive to Doppler shifts that affect the carrier frequency offset, resulting in Inter Carrier Interference (ICI). Single carrier systems show lower susceptibility as compared to multi-carrier systems.

2.3 Peak-to-Average Power Ratio (PAPR)

PAPR is measured by the envelope fluctuations of an OFDM signal. The PAPR of the transmitted OFDM symbol $x(t)$ is the ratio of peak instantaneous power to the average power of the signal, which can be mathematically represented as

$$PAPR = \frac{\max\limits_{0 \le t < NT} |x(t)|^2}{E[|x(t)|^2]} \tag{2.5}$$

where

$$E\left[|x(t)|^2\right] = \frac{1}{NT}\int_0^{NT} |x(t)|^2 dt \tag{2.6}$$

where $E[\cdot]$ denotes expectation operator. However, PTS is applied on discrete-time signals for PAPR reduction. For this reason, the discrete-time OFDM signal representation can be considered as

$$x(k) = \frac{1}{\sqrt{N}}\sum_{n=0}^{N-1} X_n e^{\frac{j2\pi nk}{LN}}, \tag{2.7}$$

where $k = 0, 1, \cdots, LN-1$. Oversampling factor is denoted by L. Since IFFT is used to generate the OFDM signal, the resulting discrete-time OFDM signal samples are obtained at the Nyquist-rate. The peak value computed using these samples may not coincide with the peak value of the continuous-time OFDM signal [32]. Hence, oversampling by a factor greater than 1 is used to increase the accuracy. It is found that the PAPR of the oversampled discrete-time signal offers an accurate approximation of the PAPR of the continuous-time OFDM signal if the oversampling factor is at least 4 [33]. Detailed discussion of the relationship between the oversampled OFDM signals PAPR and the continuous signals PAPR are represented in [34] and [35].

The performance measure for PAPR is presented using CCDF plot. The CCDF shows the probability that the PAPR of a data block exceeds a given threshold $PAPR_0$ and is computed by Monte Carlo Simulation [36]. The CCDF of the PAPR of N symbols of a data block with Nyquist rate sampling defined as

$$\begin{aligned} P_r(PAPR > PAPR_0) &= 1 - P_r(PAPR \leq PAPR_0) \\ &= 1 - (1 - e^{-PAPR_0})^N \end{aligned} \tag{2.8}$$

The CCDFs are usually compared in a graph such as Figure 2.4, which shows the CCDF of the PAPR of an OFDM signal with different sub-carriers N for 16

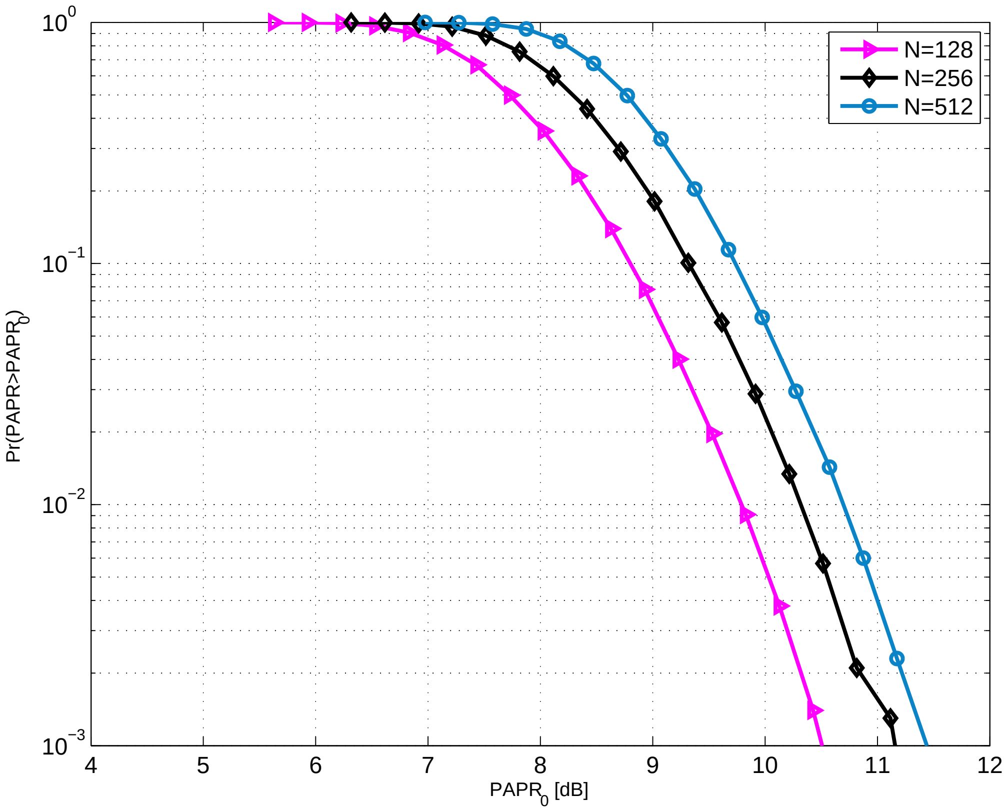


Figure 2.4: PAPR performance of 16QAM/ OFDM system when the number of sub-carrier varies

Quadrature Amplitude Modulation (QAM) with 10,000 data blocks.

2.3.1 Effects of High PAPR

Radio systems use HPA on the transmitter side to obtain maximum output power efficiency. The operating point of devices in HPA is normally at or near the saturation region to maintain power efficiency. This leads to the nonlinear characteristics of the HPA as shown in Figure 2.5, as they are very sensitive to the difference of the signal amplitudes. This amplitude difference in the OFDM sample leads to high PAPR enormously. So, high PAPR on the HPA introduces inter-modulation between different sub-carriers as well as interference into the OFDM system. This interference decreases the Bit Error Rate (BER) performance. Also, this high PAPR

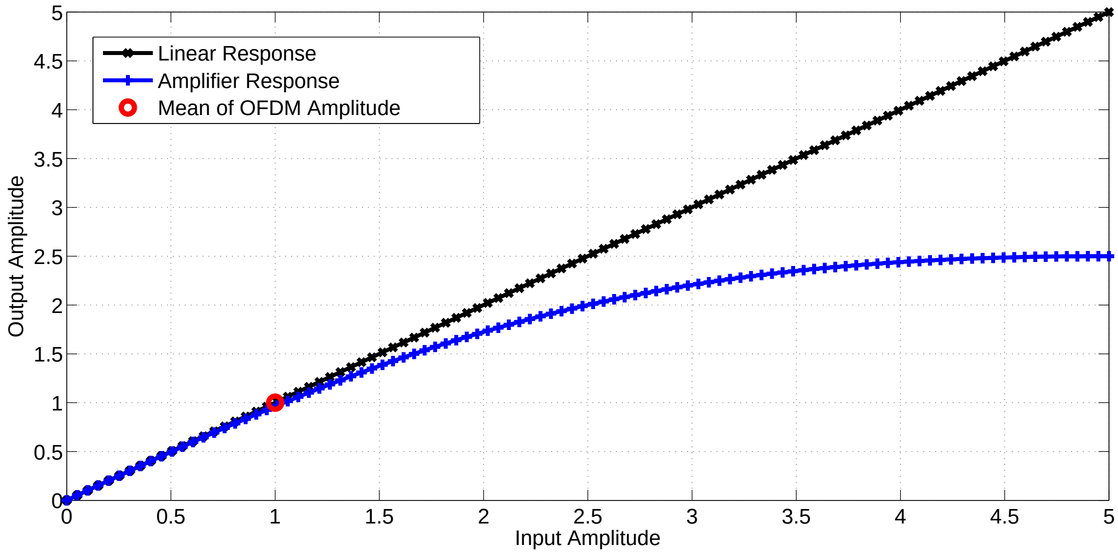


Figure 2.5: Amplifier Characteristics

forces the amplifier to operate with huge back-off the power for linear amplification of the signal. This type of linear amplifier has reduced power efficiency [11,37,38].

Digital-to-Analog Converters (DACs) should have sufficient dynamic range to accommodate the massive peaks of the OFDM signals because of the high PAPR. Even if, high precision DAC can supports high PAPR with low quantization noise, it seems to be very expensive. On the other hand, low precision DAC is cheaper with inferior quantization noise characteristics [11, 37, 38].

For systems with the large number of OFDM sub-carriers, OFDM signals follow the Gaussian distribution. In such type of distribution average of the peak signal rarely occur and uniform quantization by the Analog to Digital Converter (ADC) is not desirable. If the signal is clipped, in-band distortion and out-of-band expansion (adjacent channel interference) occurs [11, 37, 38]. The significant impact of a high PAPR includes-

- Increased complexity in the ADC and DAC.
- Reduced efficiency of Radio Frequency (RF) amplifiers.

2.4 Criterion for the selection of PAPR reduction techniques

There are many factors that should be considered before a PAPR reduction method is employed. These factors include PAPR reduction capability, power increase in the transmitted signal, computational complexity, BER performance of the receiver, loss in data rate and other considerations [11]. These factors are described briefly below:

- **PAPR reduction capability:** Careful attention must be given to the fact that some techniques while reducing PAPR results in introducing other harmful effects. The technique employed should not introduce in-band distortion and out-of-band radiation by applying the PAPR reduction techniques.

- **Low average power:** Rise in the average power in process of PAPR reduction requires a high linear operation region in HPA and hence can degrade BER performance.

- **No BER performance degradation:** The motivation of PAPR reduction is to get better system performance. The purpose of PAPR reduction should be achieved with no BER performance degradation comparable to the original OFDM system.

- **Additional power:** System power efficiency is very critical issue while considering the PAPR reduction. If the operation of the technique reduces PAPR, but needs more additional power, then it can degrade the BER performance when the transmitted signals are normalized back to the original power levels.

- **No spectral spillage:** Processing PAPR reduction technique should not destroy the inherent feature (orthogonality) of OFDM signal.

- **Computational complexity:** Computational complexity is another important consideration in choosing a PAPR reduction method, since this can pose a serious bottleneck in hardware implementation.

- **Other considerations:** Many of the PAPR reduction techniques do not consider the effect on the other components in the transmitter such as the transmit filter, digital-to-analog (D/A) converter, and transmit power amplifier. In practice, PAPR reduction techniques can be used only after careful performance and cost analysis for realistic environments.

2.5 PAPR Reduction Techniques

PAPR reduction methods can be generally classified into two domain methods: frequency domain method and time domain method. The basic notion of frequency domain method is to increase the cross-correlation coefficient of the input signal before IDFT and decrease the output of the IDFT peak value or average value. Selective Mapping (SLM), Partial Transmit Sequence (PTS), Precoding, etc. schemes are the example of frequency domain method [39]. In time domain method, PAPR is reduced by distorting the signal before amplification and addition of extra signals to increase the average power. Clipping and Filtering, Peak windowing, etc. are examples of time domain methods. Time domain methods are very simple method because they require very low computational time but introduce distortion, increase out of band radiation and also degrade BER performance. On comparing these two methods, frequency domain PAPR reduction technique is the efficient one because of its ability to compress the PAPR without distorting the transmitted signal, without in-band distortion and out-of-band radiation of

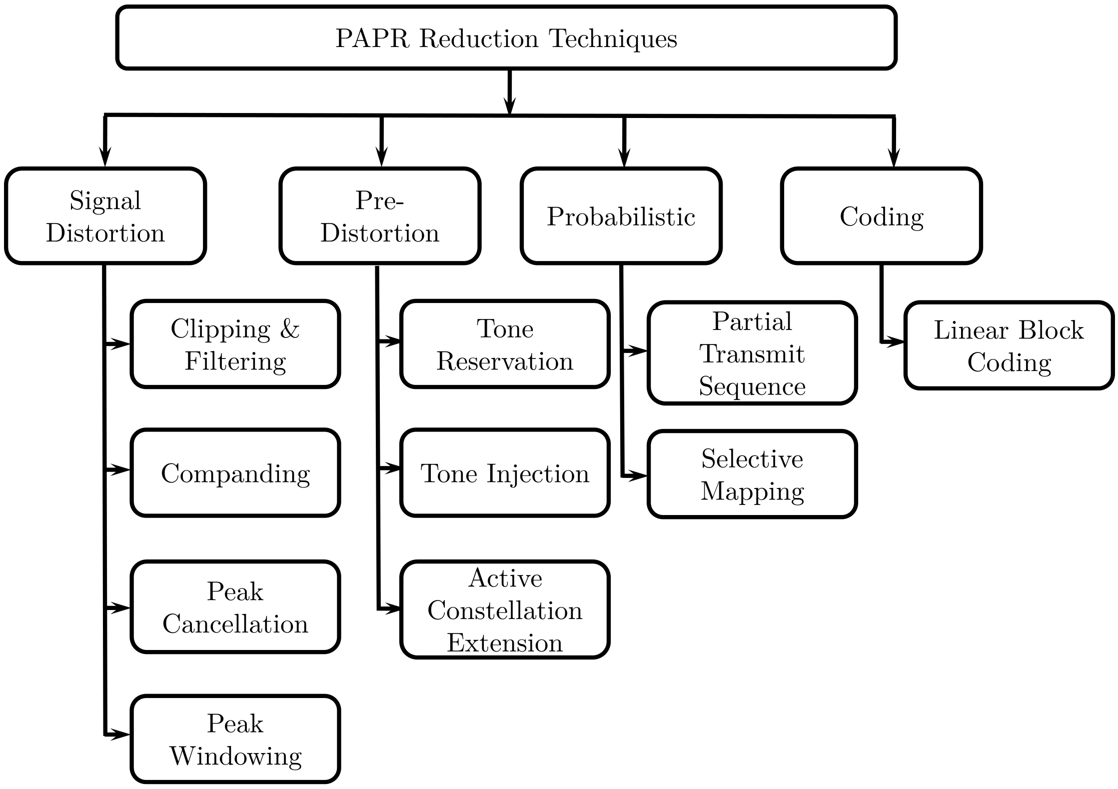


Figure 2.6: PAPR reduction techniques

the OFDM signals.

Broadly PAPR reduction techniques are classified into four sections as shown in Figure 2.6 [40].

2.5.1 Signal distortion techniques

The key concept behind this scheme is to identify high amplitude samples above predefined threshold value in transmitted envelope. The most popular signal distortion techniques are companding [41], clipping and filtering [7], peak windowing and peak cancellation [42]. These methods reduce envelope fluctuations significantly, but they cause both in-band and out-of-band distortion which leads to a rise in BER [38].

2.5.1.1 Clipping and Filtering

It is the easiest signal distortion based PAPR reduction technique [7]. This method employs a clipper that bounds the signal envelope to preset clipping level (C) if the signal surpasses that level; otherwise, the clipper offers the signal without change, defined by

$$B\left[x\left(n\right)\right]=\begin{cases} x\left[n\right] & if\left|x\left[n\right]\leq C\right| \\ C^{j\phi x[n]} & if\left|x\left[n\right]>C\right| \end{cases} \tag{2.9}$$

where C and $\phi x[n]$ are the clipping level and angle of OFDM signal $x[n]$. Clipping is a non-linear process that directs to both in-band and out-of-band distortions. The distortion causes performance degradation in terms of BER [43].

Filtering of the clipped OFDM signal can preserve the spectral efficiency by rejecting the out-of-band distortion, consequently, amending the BER performance but may cause to peak power regrowth. The process repeated clipping and filtering operations can be used to obtain a desirable PAPR at the cost of increased computational complexity [28].

Clipping is however a simplest approach to reduce sudden peaks in OFDM envelope to lower down PAPR significantly. But using a hard limit threshold introduces distortion causing adjacent channel interface and poor BER performance. Both of these problems are inevitable, rectifying these problems is a tedious task involving high cost and complexity. So clipping is not a good candidate for PAPR reduction [38].

2.5.1.2 Companding

The key idea of the companding PAPR reduction scheme is to transform the faded signal into a uniformly distributed signal. The companding transform [44] is commonly used in speech processing. Companding includes compression and expansion. Several companding methods are available in the literature [45]. Two stan-

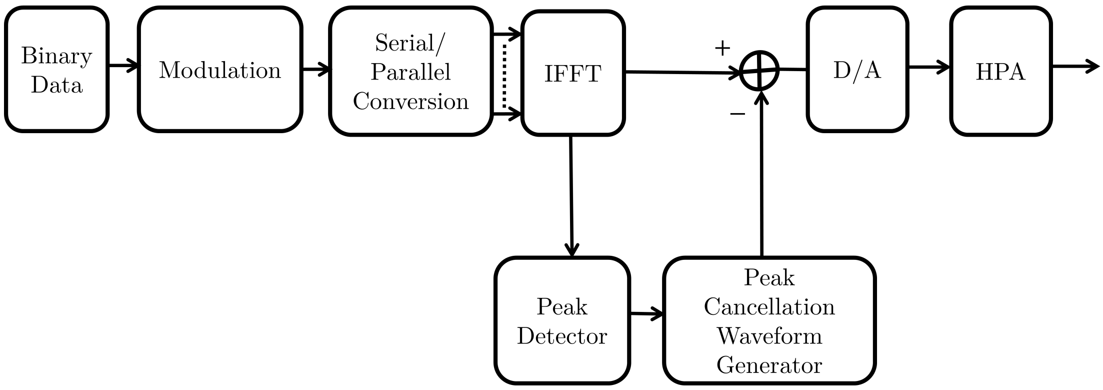


Figure 2.7: Block diagram of peak cancellation in OFDM transmitter

dard compression methods are A-law and μ-law. Companding increases smaller signal power levels and keeps larger signal value fixed to increase signal quality [37].

Since average power of OFDM signal is enhanced to reduce PAPR value, it will put additional burden on transmitter to transmit more power than before. This is a major drawback with companding scheme, and reason why it is not in much use.

2.5.1.3 Peak Cancellation and Windowing

In this technique, a peak cancellation waveform is appropriately generated, scaled, shifted and subtracted from the OFDM signal at those segments that exhibit high peaks [38]. The objective of method is to choose sample when the magnitude exceeds a certain threshold level, shown in Figure 2.7.

The process of peak windowing is an interaction of window function to OFDM symbols [42]. Unlike clipping where the predetermined threshold limits the amplitude, windowing uses weighting function to multiply with peak samples. Hamming, Hanning and Kaiser are most commonly use window functions for PAPR reduction.

2.5.2 Pre-distortion techniques

Pre-distortion technique is based on reorientation or distributing the energy of data symbol before taking IFFT [46]. The pre-distortion technique contains ability to compensate the nonlinear effect of a high power amplifier (HPA) in OFDM systems. In these methods, the constellation of OFDM signal is altered in such a way that resultant OFDM signal have low PAPR value. These methods are discussed as follows:

2.5.2.1 Tone Reservation

The key concept of tone reservation (TR) is to reserve the subset of tones for PAPR reduction [47]. The statistical vector is added to OFDM symbol for optimizing PAPR. This can be explained by following

$$\hat{x}\left[n\right] = x\left[n\right] + c\left[n\right] = IDFT\left(X + A\right) \tag{2.10}$$

where X represent OFDM symbol and A is reserved tone. Here, frequency domain processing is used for linear addition of reserved tone.

The parameter on which PAPR is testing

$$\min_{c} \|x + c\| = \min_{c} \|x + IDFT\left(A\right)\|_{\infty} \tag{2.11}$$

With the TR technique, additional power is required for transmitting the peak reduction tones (PRTs) symbols and the effective data rate decreases since the PRT tones work as an overhead.

In TR scheme data rate loss incurs due to addition of PRTs, as due to low signal-to-noise ratio (SNR) they do not carry information, thus can only solve the purpose of PAPR reduction at the cost of low data rate especially for lower value of sub-carriers N. Apart from this finding, an optimize set of PRTs increase the complexity at the transmitter, however adding PRT increases required transmission

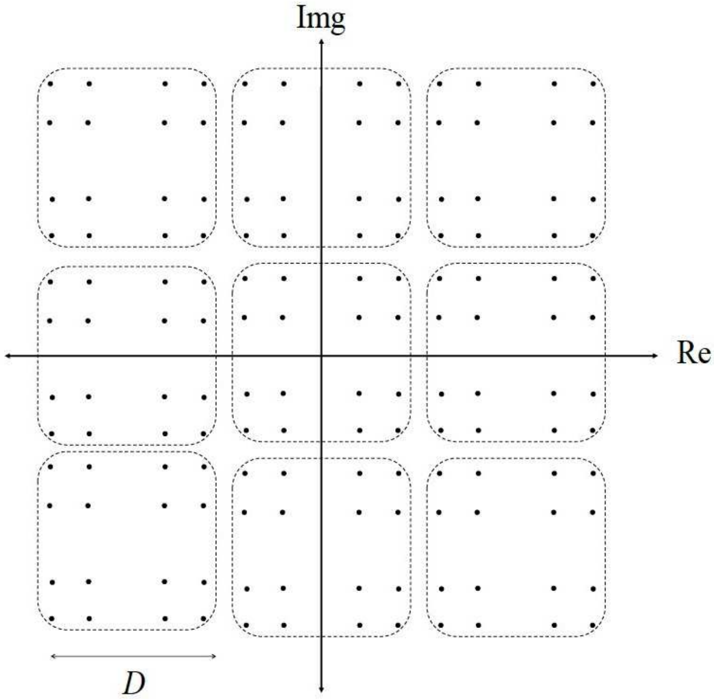


Figure 2.8: Tone injection technique for 16-QAM constellation

power.

2.5.2.2 Tone Injection

The philosophy of tone injection (TI) technique is to enlarge the constellation size so that every point in the original complex plane constellation is mapped onto various other points in the expanded constellation prior to IDFT processing [48].

Figure 2.8 shows QAM constellation with the original constellation size as C, and its points are spaced by d, then its equivalent points in the expanded constellation should be

$$D = \rho d \sqrt{C} \tag{2.12}$$

with $\rho \geq 1$, where D is a fixed constant.

D is an important parameter as it affects the transmission power as well as the

BER. Higher value of D increases the average power but BER will be low, lower value of D causes poor BER as constellation points come close to each other. Here,

$$X_n = X + pD + j.qD \tag{2.13}$$

where p and q are integers as this describes how a symbol X is modified for transmission with p and q being chosen to minimize PAPR. In TI scheme, unlike TR scheme there is no data rate loss, no side information is required and only Mod-D operation is required to decode the signal back. TI scheme also require high transmission power due to addition of tones [49].

2.5.2.3 Active Constellation Extension

Active constellation extension (ACE) is a pre-distortion PAPR reduction technique [46]. The key idea of this method is to dynamically extend the outermost signal constellation points of the modulated symbols towards outside of the original constellation which leads to an alternative representation of the same symbol. ACE however offers dual advantage of PAPR and BER reduction [11]. ACE scheme do not require transmission of side information too, so there is no data rate loss too. But the major disadvantage is the increase in transmission power. Thus, the use of this scheme is limited to smaller constellation size only.

2.5.3 Signal scrambling (Probabilistic) techniques

The probabilistic (scrambling) technique is to scramble an input data block of the OFDM symbols and transmit one of them with the minimum PAPR so that the probability of incurring high PAPR can be reduced [50, 51]. While the technique does not suffer from the out-of-band power, the spectral efficiency decreases and the complexity increases as the number of sub-carriers increases [52]. Furthermore, the technique fails to guarantee the PAPR below a specified level [53].

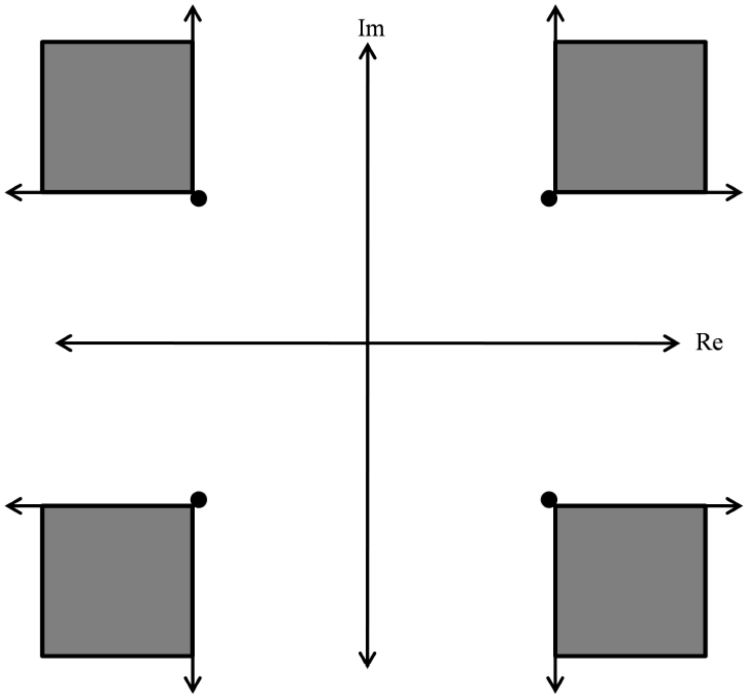


Figure 2.9: Constellation distribution of ACE PAPR reduction method

2.5.3.1 Partial Transmit Sequence

The partial transmit sequence (PTS) method developed by Muller and Huber in 1996, presents an efficient method for phase factor computation [33, 36]. In PTS technique, an input data block of length N is divided into M number of disjoint sub-blocks [9]. Consequently, the IDFT is computed for each sub-block and weighted by a phase vectors $b_m = e^{j\phi_m}$, where $\phi_m \in (0, 2\pi)$ and $m = 1, 2, \cdots M$. The check operation is performed with equal number of candidate sequence, to get minimum PAPR symbol from original signal. The phase vectors are then optimized such that the PAPR of the combined signal is minimized. The complexity of PTS depends on the number of sub-blocks M and the allowed phase vectors. Section 2.6 depicts a block diagram of the OFDM transmitter with PTS technique. Therefore, the search complexity increases with the number of sub-blocks. At receiver, the

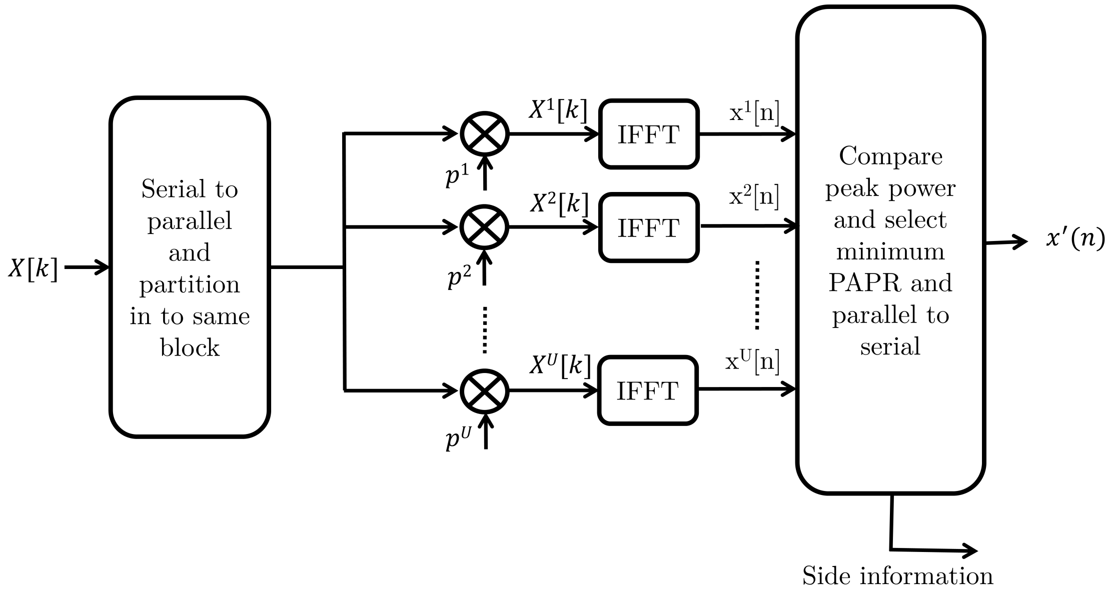


Figure 2.10: Block diagram of selective mapping (SLM) technique for OFDM transmitter.

inverse phase vector is applied to recover the original sub-carrier sequence.

2.5.3.2 Selective Mapping

The key idea behind selective mapping (SLM) [10] is simple, that is to divide data symbol into sub-blocks and multiply them with different phase rotation sequences. Following this, the symbol having minimum peak power symbol among all sub-blocks is selected [10, 54]. Phase rotations U are generated as

$$p^U = \{p^u(k), k = 0, 1, \cdots, N\}, u = 0, 1, \cdots, U - 1 \tag{2.14}$$

where $p^u(k) = e^{(\varphi^u(k))}$, $j = \sqrt{(-1)}$ and $\varphi^u(k) \in [0, 2\pi]$. The input data block X_{N_T} is multiplied by p^u to generate the signal $X^u_{N_T}$ as

$$X^u_{N_T} = p^u(k) X_{N_T}(k) \tag{2.15}$$

After SFBC encoding the signal $X^u_{N_T}$ are transformed into time domain signal

$x_{N_T}^u$, via the IFFT operation and the optimal set of lowest PAPR is chosen as

$$\hat{u} = \arg \min_{0 \leq u \leq U-1} \left(\max_{i=1,2} \max_{0 \leq n \leq LN-1} \left| x_i^u (n) \right| \right) \tag{2.16}$$

Figure 2.10 shows the block diagram of SLM techniques. In general, the U phase rotation sequence P^u should be transmitted to the receiver as the SI with $log_2 U$ bits.

All the probabilistic techniques mentioned above are however distortion less techniques, but all of them have some serious implementation issues. PTS and SLM require transmission of side information causing reduced bandwidth efficiency and data rate loss. All the above schemes also suffers from optimization problem in scrambling the best PAPR candidate. Computational complexity also makes implementation a tedious task.

2.5.4 Coding techniques

A coding technique is a method to employ some error correcting codes for PAPR reduction [35]. Processing are applied before the generation of OFDM signal (before IFFT). When N signals are added with the same phase, they produce a peak power, which is N times the average power. The basic idea of all coding schemes for reduction of PAPR is to reduce the probability of occurrence of the same phase of many signals. The coding methods select such code words that minimize or reduce the PAPR. The technique does not introduce distortion and does not create out of band radiation, however the system suffers in terms of bandwidth efficiency as the code rate decreases. This technique also suffers from the curse of complexity to find the best codes and store large lookup tables for encoding and decoding, especially when the number of sub-carrier is large. The error correcting codes like block codes, cyclic codes, Golay complementary sequence, Reed-Solomon (RS) code, Reed-Muller (RM) code, Hadamard code and Low Density Parity Check

(LDPC) code can be used [8, 55–57].

Table 2.2: Comparison of features of different PAPR reduction techniques

Methods	**Distortion-less**	**Power increase**	**Data rate loss**	**Required processing at transmitter (Tx) and receiver (Rx)**
Clipping [7]	No	No	No	Tx: Amplitude clipping, filtering Rx: None
Tone Reservation [47]	Yes	Yes	Yes	Tx: IDFTs, find value of PRCs Rx: Ignore non-data-bearing sub-carriers
Tone Injection [48]	Yes	Yes	No	Tx: IDFTs, search for maximum point in time, tones to be modified, value of p and q Rx: Modulo-D operation
Active Constellation Extension (ACE) [46]	Yes	Yes	No	Tx: IDFTs, projection onto "shaded area" Rx: None
Coding [8]	Yes	No	Yes	Tx: Encoding or table search Rx: Decoding or table search
Interleaving [58]	Yes	No	Yes	Tx: K IDFTs, $(K-1)$ interleavings Rx: Side information extraction, inverse interleaving
Partial Transmit Sequence (PTS) [36]	Yes	No	Yes	Tx: M IDFTs, W^{M-1} complex vector sums Rx: Side information extraction, inverse PTS
Selective Mapping (SLM) [10]	Yes	No	Yes	Tx: U IDFTs Rx: Side information extraction, inverse SLM

Coding techniques suffer from a major problem of exhaustive search to find a suitable code which can reduce PAPR but at the same time these methods are limited to a small number of sub-carriers owing to high complexity of the

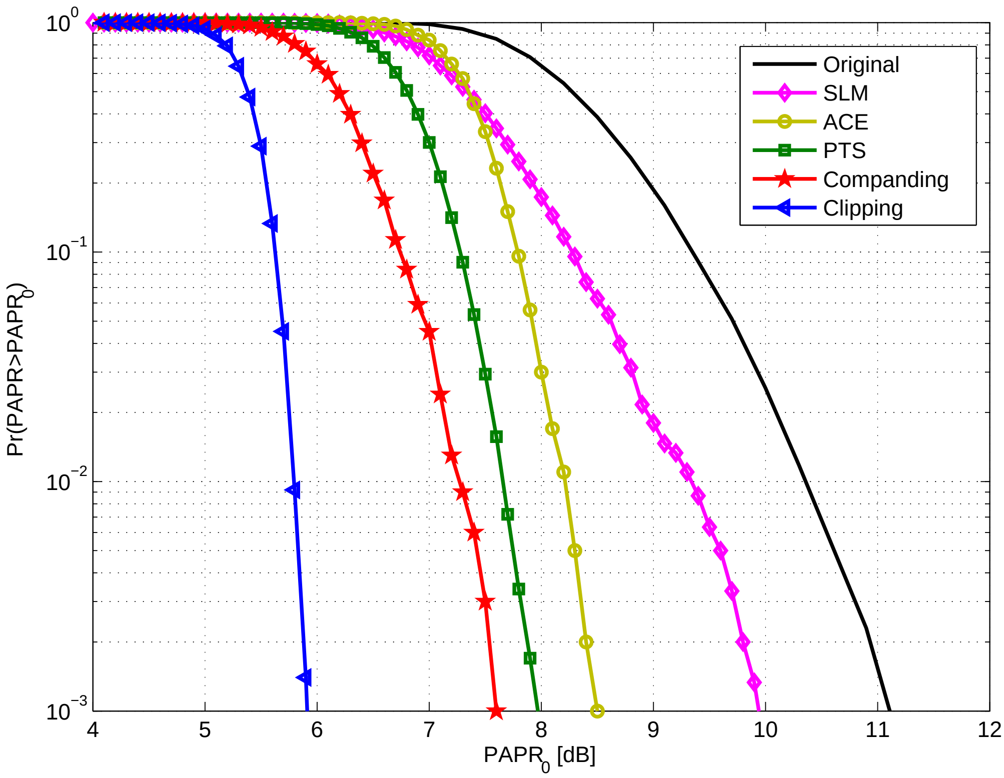


Figure 2.11: Comparison of CCDF for different PAPR reduction techniques

encoder and decoders. These methods find it difficult to exploit the error correction capability and PAPR reduction at the same time.

Figure 2.11 shows the comparison of CCDF for different PAPR reduction techniques for OFDM system. In Table 2.2, we summarize the features of different PAPR reduction techniques [11]. In all the above mentioned techniques, active constellation extension (ACE) and partial transmit sequence (PTS) are found to be most suitable for PAPR reduction especially in the latest technology such as 4G, LTE, WLAN and WiMAX systems. However, it also has certain issues such as transmission power requirement, high computational complexity, and need of side information.

2.6 Partial Transmit Sequence Technique for PAPR Reduction

Figure 2.12 shows the block diagram of the OFDM transmitter with the PTS technique. All of the techniques described below can be implemented by appropriately changing the phase optimization block.

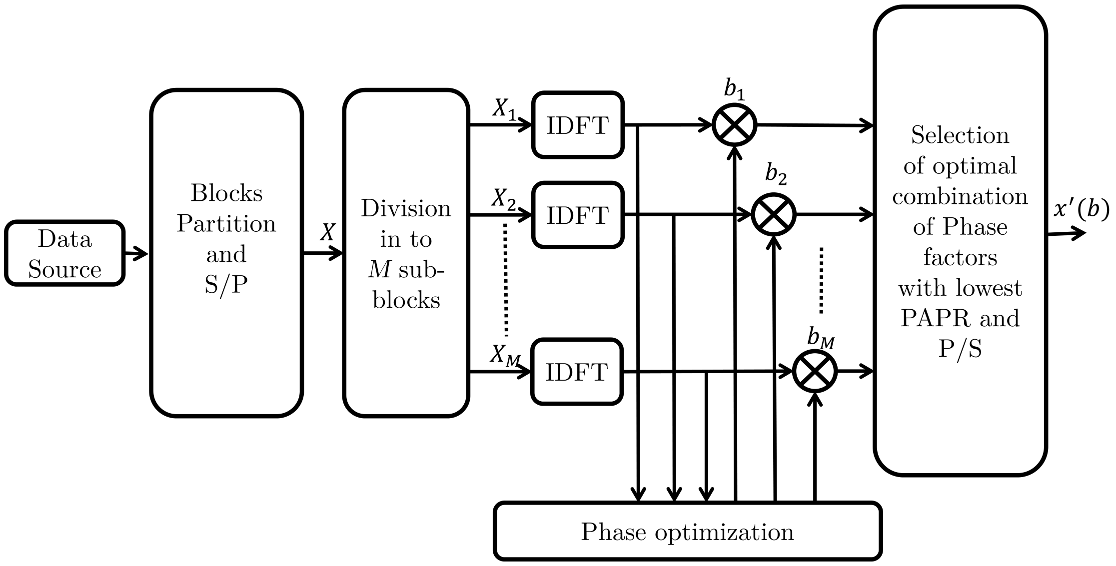


Figure 2.12: The block diagram of Traditional Partial Transmit Sequence technique

2.6.1 Ordinary Partial Transmit Sequence (OPTS)

The main idea of following scheme is describe as:

2.6.1.1 Partitioning of Sequence

In ordinary PTS technique, the input data block X of length N is partitioned in to M disjoint sub-blocks $X_m = [X_{m,1}, X_{m,2}, \cdots X_{m,N}]^T$, where $m = 1, 2...M$, such that

$$\sum_{m=1}^{M} X_m = X \tag{2.17}$$

and the sub-blocks are combined to minimize the PAPR in the time domain. The L-times oversampled time-domain signal of X_m is denoted as x_m, $m = 1, 2, \cdots, M$, is denoted as $x_m = [x_{m,1}, x_{m,2}, \cdots x_{m,NL}]^T$, where $m = 1, 2...M$, which are obtained by taking an IDFT of length NL on X_m concatenated with $(L-1)N$ zeros. These are called as the Partial Transmit Sequences (PTS).

2.6.1.2 Phase Optimization

Complex phase factors, $b_m = e^{j\phi_m}$, where $\phi_m \in (0, 2\pi)$ and $m = 1, 2, \cdots M$, are introduced to combine the partial transmit sequences. We shall write the set of the phase factors as a vector $b = [b_1, b_2, \cdots b_M]^T$. The time-domain signal sample after combining is given by

$$x'(b) = \sum_{i=1}^{M} b_m \cdot x_m \tag{2.18}$$

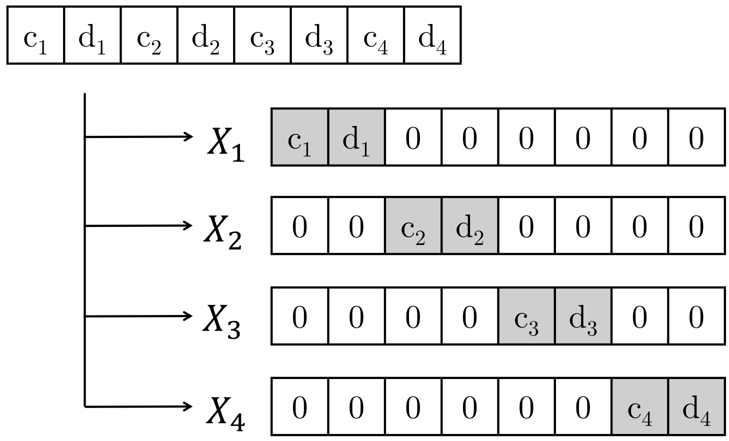
where $x'(b) = [x'_1(b), x'_2(b), ..., x'_{NL}(b)]^T$

2.6.1.3 Optimal Combination of Phase Factors

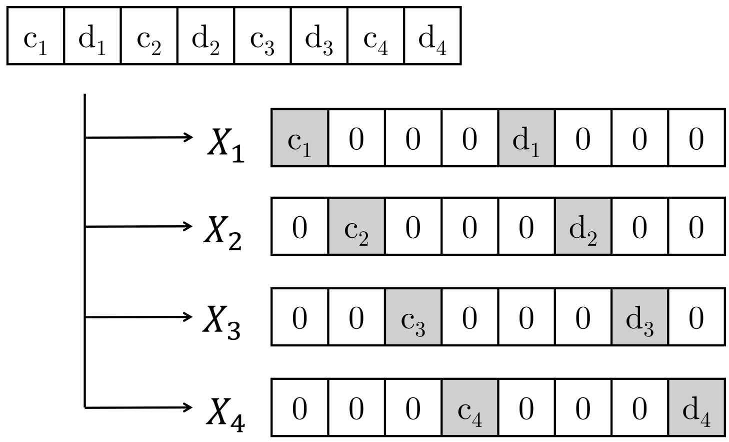
The goal of the PTS approach is to find an optimal phase-weighted combination to minimize the PAPR. In general, the selection of the phase factors is limited to a finite set of elements to reduce the search complexity. The set of allowed phase factors can be represented as

$$P = \left\{ e^{j2\pi l/W} | l = 0, 1, \cdots, W-1 \right\} \tag{2.19}$$

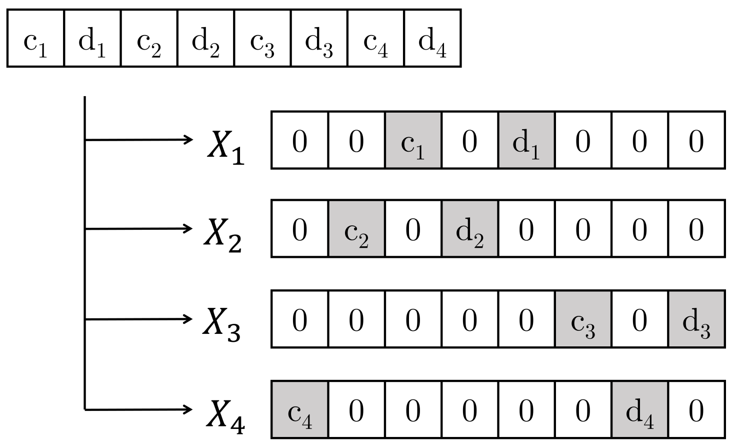
Where W is the number of possible phase factors. In addition, we can set b_1 = 1 without any loss of performance. So, we perform an exhaustive search for $(M-1)$ phase factors. Hence, W^{M-1} sets of phase factors are searched to find the optimum set of phase factors. The search complexity increase exponentially with the number of sub-blocks M [59].



(a) Adjacent sub-block partitioning technique



(b) Interleaved sub-block partitioning technique



(c) Pseudo-random sub-block partitioning technique

Figure 2.13: PTS sub-block partitioning technique

Sub-block partitioning is a method of division of sub-bands into multiple disjoint sub-blocks. There are three kinds of sub-block partitioning scheme popularly used: Adjacent, interleaved and pseudo-random partitioning [53]. For the interleaved sub-block partitioning scheme, every sub-band signal spaced L apart is allocated to a sub-block. In the adjacent scheme, N/L successive sub-bands are assigned into one sub-block sequentially. Each sub-band signal is assigned into any one of the sub-blocks randomly in the pseudo-random scheme [60]. Of these, pseudo-random partitioning has been found to provide good performance in terms of PAPR reduction [40]. For example, if we consider a signal $X = [c_1, d_1, c_2, d_2, c_3, d_3, c_4, d_4]$, then possible combination of sub-block partitioning in the PTS scheme are shown in Figure 2.13. If the number of sub-blocks $M = 4$ and the set of phase weighing factors is {1,-1} (i.e. $W = 2$), then all the phase weighing factor sequences, identified by $B_1, B_2, \cdots, B_8$ are shown in Table 2.3. For searching optimum combination of phase weighing factor, we need to multiply X_1 with $B_1, B_2, \cdots, B_8$, similarly X_2 with $B_1, B_2, \cdots, B_8$ and so on up to X_4. After that we will calculate PAPR of the signal $[X_1 \cdot B_1]$, $[X_1 \cdot B_2]$ and so on. Suppose the signal $[X_1 \cdot B_1]$, $[X_2 \cdot B_1]$, $[X_3 \cdot B_1]$ and $[X_4 \cdot B_1]$ are having lowest PAPR value, then transmitted OFDM signal x' will be

$$x' = [X_1 \cdot B_1] + [X_2 \cdot B_1] + [X_3 \cdot B_1] + [X_4 \cdot B_1]$$

The performance of PAPR reduction is directly proportional to the number of phase weighting factors. However, when the number of phase weighting factors is large, the number of parallel addition processor and the number of phase weighting factor sequences need a complex computation to find the optimum set of phase weighing factor and it leads to a heavy load for the system. The PAPR reduction performance in PTS is governed by two factors - one is the sub-block partition style and the other is the value of phase weighting factor set. Therefore, the sub-block

Table 2.3: All the phase weighing sequences for W=2 and M=4

	Phase weighing sequence		Phase weighing sequence
$\boldsymbol{B_1}$	$\{1, \ \ 1, \ \ 1, \ \ 1\}$	$\boldsymbol{B_5}$	$\{1, -1, -1, -1\}$
$\boldsymbol{B_2}$	$\{1, \ \ 1, \ \ 1, -1\}$	$\boldsymbol{B_6}$	$\{1, -1, -1, \ \ 1\}$
$\boldsymbol{B_3}$	$\{1, \ \ 1, -1, \ \ 1\}$	$\boldsymbol{B_7}$	$\{1, -1, \ \ 1, -1\}$
$\boldsymbol{B_4}$	$\{1, \ \ 1, -1, -1\}$	$\boldsymbol{B_8}$	$\{1, -1, \ \ 1, \ \ 1\}$

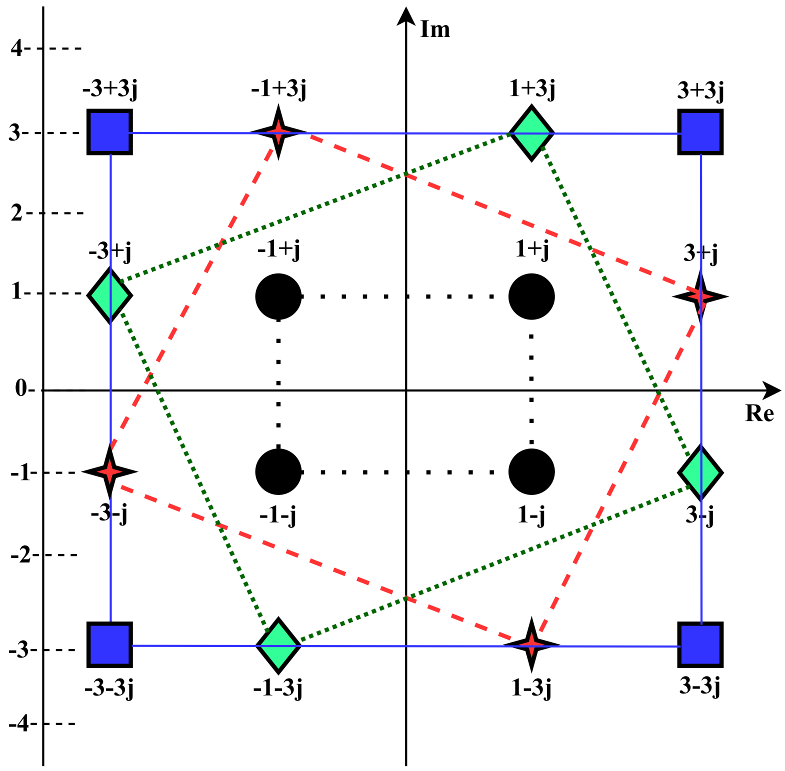


Figure 2.14: Mapping of quaternary data to 16-QAM constellation using 4 phase factors in PTS technique

partition style and the value of phase weighing factor set could be well designed to obtain the candidate signals with reducing correlation to improve PAPR reduction performance. An effective PAPR reduction technique could be investigated based on the trade-off between the phase weighing factor and sub-block partitioning. [61].

Table 2.4: Quaternary 16-QAM constellation mapping using phase rotation factors (1, j, -1, -j)

Quaternary data	Initially Mapped Quaternary data points to 16 QAM Constellation	Constellation points after multiplication with phase factors in S			
		1	j	-1	-j
0	3+3j	3+3j	-3+3j	-3-3j	3-3j
1	-3+j	-3+j	-1-3j	3-j	1+3j
2	-1-j	-1-j	1-j	1+j	-1+j
3	1-3j	1-3j	3+j	-1+3j	-3-j

2.6.1.4 Quaternery to 16-QAM mapping

In this scheme, the quaternary data points are initially mapped to four different constellation points of 16-QAM using Table 2.4. It can be seen from Figure 2.14, that quaternary data points (0, 1, 2 and 3) are initially mapped to four different constellation points located at {3 + 3j, - 3 + j, -1- j, 1- 3j} and are denoted by square, diamond, circle and star respectively. It is noteworthy that initially mapped constellation points are lying in four different quadrants. The constellation points {3 + 3j, - 3 + j, -1- j, 1- 3j} after multiplication with phase rotation factor W={1, j, -1,-j}, are rotated by $\{0, \pi/2, \pi, 3\pi/2\}$ as shown in Figure 2.14 and covers all 16 points of 16-QAM constellation. Any initially mapped quaternary data point after multiplication with phase factor {1, j, -1,-j} lies on the vertices of a square. The constellation points are unique and can be de-mapped to obtain the quaternary data signal using Table 2.5. Hence, as per Table 2.5, if any of the data point is received as {3 + 3j, - 3 + 3j, - 3 - 3j or 3 - 3j}, {-3 + j, -1- 3j, 3 - j or 1+ 3j}, {-1- j, 1- j, 1+ j or -1+ j} or {1- 3j, 3 + j, -1+ 3j or - 3 - j} then it will be de-mapped to constellation the constellation points {3 + 3j, - 3 + j, -1- j, 1- 3j} respectively, and these are nothing but the four initially mapped quaternary data points 0, 1, 2 or 3 respectively.

The de-mapping scheme does not require any side information (SI) about the

Table 2.5: De-mapping of 16-QAM constellation symbols to quaternary data points

Demodulated Constellation symbols	De-mapped Constellation Point	Recovered Quaternary data
{3 + 3j, - 3 + 3j, - 3 - 3j or 3 - 3j}	3+3j	0
{-3 + j, -1- 3j, 3 - j or 1+ 3j}	-3+j	1
{-1- j, 1- j, 1+ j or -1+ j}	-1-j	2
{1- 3j, 3 + j, -1+ 3j or - 3 - j}	1-3j	3

phase rotation factors at the receiver, thus, eliminating the major constraints of PTS technique. This approach extends the constellation size but does not result any data rate loss because each quaternary data point corresponds to only one 16-QAM symbol sent over each sub-carrier, which keeps the bandwidth requirement unchanged.

The criteria for choosing the set of four points (out of eight) for initial mapping of quaternary data may be stated as follows:

- Any constellation point (P) can be picked randomly out of eight available points for mapping of quaternary data 0.
- For a chosen point P, the constellation point located at a phase angle of $\pi/2$ radians is eliminated from the choices of initial mapping of remaining three quaternary data points, because it results after multiplication of point P with phase factor j.
- For a chosen point P, the constellation point located a π radians should be chosen for initial mapping of any remaining quaternary data to avoid peak formation as discussed above.
- Repeat the steps 2, 3 till all four quaternary data points initially map on the 16-QAM constellation.

2.6.2 Iterative Partial Transmit Sequence (IPTS)

As shown in Figure 2.12, the conventional PTS scheme requires an exhaustive search over all combinations of allowed phase weigh factors; leading to an exponential rise in the number of sub-blocks. Following this, the search complexity increases exponentially with the number of sub-blocks. In the literature [52,62–64], various schemes have been proposed to reduce this complexity.

In contrast for complexity reduction, a novel suboptimal Iterative Partial Transmit Sequence (IPTS) as described in [9] is adopted in this thesis; which uses the binary phase factors of $\{1,-1\}$. This technique can be summarised in the following steps:

1. Partition the input data block in to M sub-blocks as in (2.17).
2. Set all the phase factors b_i=1 for i=1 ...M. Find $PAPR$ of equation 2.18, and set it as $PAPR_{min}$.
3. Set i=2
4. Modify the first phase vector b_i= -1 and recalculate the new $PAPR$ with equation 2.18.
5. If $PAPR > PAPR_{min}$, switch b_i back to 1. Otherwise, update $PAPR_{min} = PAPR$.
6. If $i < M$, increment i by one and go back to step 4. Otherwise, exit this process and finally transmit the optimal phase sequence with minimum PAPR.

The number of computations for (2.18) in this IPTS technique is equal to number of sub-block M, which is much fewer than that required by the conventional PTS technique.

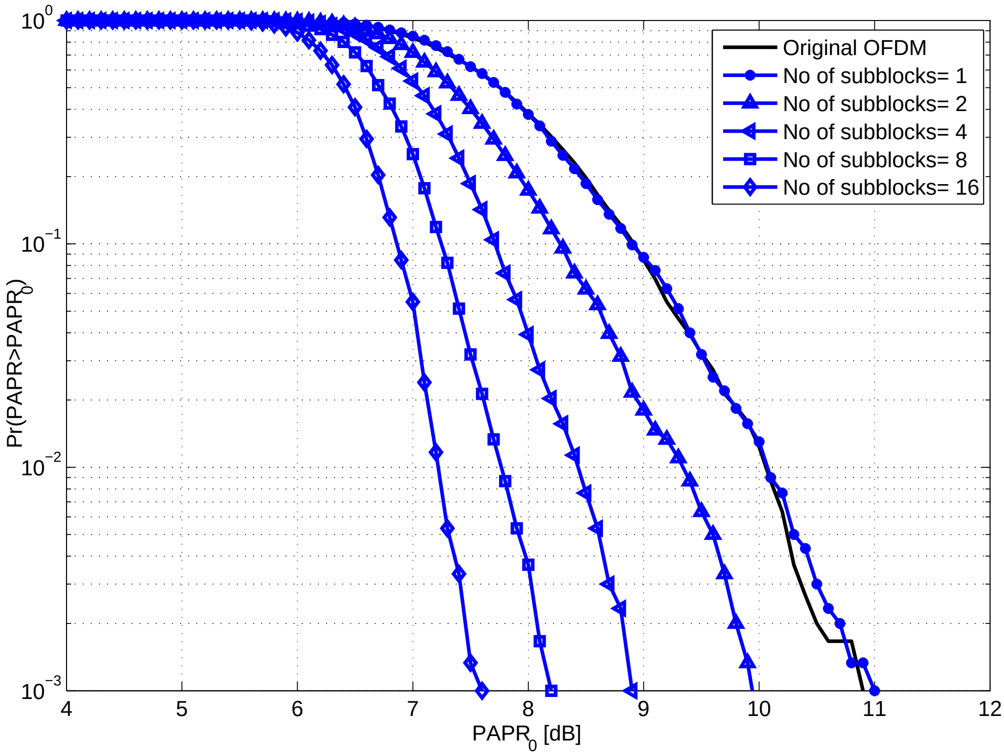


Figure 2.15: PAPR performance of 16QAM/ OFDM system with IPTS Technique when the number of sub-block varies

Figure 2.15 shows CCDF of PAPR for a 16QAM/OFDM system using IPTS, as the number of sub-block varies with sub-carriers N=256 and 3000 data blocks. It can be seen that PAPR performance improves as the number of sub-block increases with M= 1, 2, 4, 8, and 16. For 1 disjoint subset (i.e. M=1), the PAPR is calculated around 10.9 dB at CCDF of 10^{-3} , for 2 disjoint subsets (i.e. M=2), PAPR observed is approximately 9.8 dB at CCDF of 10^{-3}, for 4 disjoint subsets (i.e. M=4), the calculated PAPR is approximately 8.9 dB and for 8 disjoint subsets (i.e. M=8), the calculated PAPR is approximately 8.2 dB at CCDF of 10^{-3}. Similarly, for 16 disjoint subsets (i.e. M=16), PAPR) is 7.6 dB at CCDF of 10^{-3}. From the above simulation results, it can be deduced that, for more subsets the PAPR is less. Alternatively, PAPR reduction capability increases with increasing number of sub-blocks [40].

2.7 Review of optimization algorithms for PTS based PAPR reduction

The conventional PTS scheme is an efficient and distortion-less technique for PAPR reduction, which optimally combines signal sub-blocks. The objective of the PTS scheme is to implement an optimal phase vector for the sub-block set that minimizes the PAPR [36]. Design of the optimum phase factor from a set of known solutions is challenging, because it is a complex, non-linear optimization problem. The exhaustive search space for optimal phase factor rises exponentially with the number of sub-blocks in PTS [65]. The two main demerits of the PTS are as follows- First one is a high complexity. High complexity occurs when PTS search for optimal phase factor. This technique needs a complete search over all combinations of the allowed phase weighting factors. Furthermore, the searching process increases exponentially with the number of sub-blocks. The second one is to transmit the side information and to recover the side information at the receiver side safely.

2.7.1 Evolutionary Algorithms based PTS Optimization

Evolutionary optimization techniques have attracted attentions of researchers in the last two decades to obtain the desirable PAPR reduction with a low computational complexity [66–69]. Some of these techniques includes Particle Swarm Optimization [13], Genetic Algorithm [14], Artificial Bee Colony Algorithm [15], Differential Evolution algorithm [16], Harmony Search [17] etc. Although the optimization techniques to PTS methods have shown PAPR reduction performance for OFDM systems, the technique uses all the samples of each candidate signal for peak power reduction [18]. A novel sub-block partition scheme (SPS) for the PTS technique was proposed by Seong Geun Kang et al. in 1999 [60]. Partitioning of sub-blocks are done by three methods: interleaved, adjacent and pseudo-random partition. In the proposed method, each sub-block is formed by continuous copy and concatenating signals. The proposed method is a combination of the the pseudo-random and interleaved partition scheme. The PAPR reduction performance of proposed method is almost same as the conventional pseudo-random PTS, but the computational complexity is reduced significantly. This made the scheme suitable for modern wireless communication. L. J. Cimini and N. R. Sollenberger in 2000 [9] proposed a suboptimal scheme for combining the PTS with $\{\pm 1\}$ weighting factors only. This suboptimal algorithm was based on iterative flipping. This drawback of the ordinary PTS technique was removed via this method as an optimization problem. In this technique, terminating threshold is set so that PAPR can be easily reduced. After fixing this threshold level, the process of searching is terminated as soon as PAPR drops below threshold rather than searching all the combination. Another feasible algorithm for computing the optimal PTS phase factors was proposed in 2005 by Ali Alavi, Chintha Tellambura and Ivan Fair [70]. This algorithm searches only those phase vectors that guarantee that the PAPR is bounded. This algorithm was based on Shortest Vector Problem (SVP) in a lattice that has to find the shortest non-zero vector in the lattice. The premise of Fincke and Phost sphere decoder algorithm was used to solve SVP.

In the next, Tao Jiang, Weidong Xiang, Paul C. Richardson, Jinhua Guo, and Guangxi Zhu reported a Simulated Annealing (SA) method to search the phase factors for PTS to obtain almost same PAPR as that of optimal PTS with low complexity in 2007 [63]. Their PTS scheme utilized SA's basic properties for global optimization for massive combination problems. Global optimization accepts increased trials to shun early convergence to local optimum solutions. In 2009, Jung

Chien Chen [71] proposed Cross Entropy (CE) algorithm for PTS to reduce PAPR at affordable computational complexity. The objective of CE algorithm was to find phase factor optimally. According to this method, first a score function is defined as the amount of the PAPR, following that, this score function is overset into a stochastic approximation problem. Now, this problem could be solved efficiently. The CE algorithm PTS method achieves almost same PAPR performance as compared to conventional PTS method with low complexity as shown by simulation results. Another lower complexity PAPR reduction technique was reported by Jung Chien Chen in 2010 [65]. He proposed an Electromagnetism-like (EM) algorithm for PTS, a stochastic optimization approach, to achieve considerable PAPR reduction with low complexity. The EM algorithm has four processes: (1) initialization, which generates random samples within the boundary of number of sub-blocks and iteration, (2) local search procedure is used to search optimum phase factor, (3) calculation of total force procedure is used to calculate phase factor that combine with subblocks for low PAPR and rejects others, (4) movement of the particles procedure is used to update phase factor from number of sub-blocks. A new approach to reduce the complexity of PTS scheme using a cost function was proposed in 2010 by Sheng. Ju. Ku et al., [72]. In this scheme, a new cost function was created which was defined as the sum of the power samples after taking IFFT in each sub-block. The samples with the cost function that are greater than or equal to a fixed threshold were selected. As a consequence, the signal with lowest PAPR for transmission was chosen from the selected candidates. This scheme could achieve approximately the same PAPR as of the CPTS scheme with less computational complexity.

In 2010, Yajun Wang et al., [15] proposed an Artificial Bee Colony (ABC) algorithm for reducing the phase complexity. For the high number of sub-blocks, ABC algorithm reduced computational complexity effectively. The searching capacity of the combination of phase factor is generally high. As the algorithm had only three control parameters, it was easy to adjust. In the same year, Jung Chien Chen proposed Quantum-inspired Evolutionary Algorithm (QEA) which reduces the searching process for finding the optimal phase factors [73]. Like in the evolutionary algorithms, the evolution function, and the population dynamics parameters were used to characterize the QEA. Also, QEA follows the concept of a generational population based search scheme in the same way as the genetic algorithm. In the year 2011, three relevant works were reported for low complexity PAPR reduction techniques. Jun Hou et al., [74] proposed a novel scheme for PTS, the proposed scheme had potential to achieve the similar reduction in PAPR as compared to the PTS scheme with lower computational complexity. Lingyin Wang and Ju Liu [75] proposed a method that reduces the complexity by combining Grouping Phase Weighting (GPW) and Recursive Phase Weighting (RPW) methods. The combination of these two methods provided low complexity for searching the phase factors than CPW and RPW individually. Also, it could achieves same PAPR as conventional PTS. The third work was proposed by Pooria Varahram and Borhanuddin Mohd Ali [76] for an optimal PTS method that reduced the IFFT operations. In this technique, random phase factors was multiplied with the input signal. This method reduced the complexity by decreasing the number of IFFT operation to about half. In 2012, Hojjat Salehinejad and Siamak Talebi [17] introduced an approach for peak-to-average power ratio (PAPR) reduction of such signals based on novel global harmony search (NGHS) and partial transmit sequence (PTS) schemes. With respect to the fast implementation and simplicity of NGHS technique, a significant reduction of PAPR was shown. A modified ABC-PTS (artificial bee colony-partial transmit sequence) for PAPR reduction was proposed by Xiangyu Yu, Shuai Li, Zhu Cong Zhu and Tao Zhang in 2013 [77]. Inspired by the idea of the particle swarm optimization algorithm, a global best solution was introduced into the original ABC algorithm, and the updating equation was modified with the introduction of a learning factor to consider the balance between the ability of exploration and exploitation of the algorithm. Simulation results have showed that the proposed approach has lower PAPR than the traditional ABC-PTS algorithm with the same complexity while having lower bit error rate.

Another novel scheme which was based on a stochastic optimization technique called modified differential evolution, to search the optimal combination of phase factors with low complexity was proposed by Chien-Erh Weng, Chuan-Wang Chang, Chuang-Hsien Chen and Ho-Lung Hung in 2013 [78]. Simulation results showed that these schemes could achieve significant reduction in computational complexity while keeping good PAPR reduction. In 2014, Li Li, Daiming Qu and Tao Jiang [79] proposed a joint decoding scheme to recover low-density parity-check (LDPC) codeword and partial transmit sequence (PTS) phase factors, for OFDM systems with a low peak-to-average power ratio (PAPR). Here, an optimization problem was formulated to improve the joint decoding performance by optimizing the partition. Simulation results showed that the joint decoding scheme with the proposed partition algorithms provided satisfactory error-correcting performance for a larger number of PTS groups than does with the pseudo-random partition. Wei Xiao, Honggui Deng, Fangqing Jiang, Kaicheng Zhu and Linzi Yin proposed a partial transmit sequence (PTS) technique based on the combination of a genetic algorithm (GA) and a hill-climbing algorithm (GH-PTS) to solve the problem of high PAPR in 2015 [80]. GH-PTS is a modified PTS technique based on GA-PTS. Simulation results showed that the optimized method could reduce PAPR more efficiently without any loss of bit error rate performance than the GA-PTS technique in VLC-OFDM system.

Table 2.6: Major contribution to PTS based PAPR reduction in OFDM

Year	Author(s)	Contribution
1999	Seong Geun Kang et al. [60]	Novel sub-block partition scheme (SPS) for the PTS
2000	L. J. Cimini and N. R. Sollenberger in 2000 [9]	Suboptimal scheme for combining the PTS with iterative flipping
2005	Ali Alavi, Chintha Tellambura and Ivan Fair [70]	Computing the optimal PTS phase factors based on Shortest Vector Problem (SVP)
2007	Tao Jiang, Weidong Xiang, Paul C. Richardson, Jinhua Guo, and Guangxi Zhu [63]	Simulated Annealing (SA) method for optimal PTS with low complexity
2009	Jung Chien Chen [71]	Cross Entropy (CE) algorithm for PTS to reduce PAPR at affordable computational complexity
2010	Jung Chien Chen [65]	Electromagnetism-like (EM) algorithm for PTS
2010	Yajun Wang et al. [15]	Artificial Bee Colony (ABC) algorithm for reducing the phase complexity
2010	Jung Chien Chen [73]	Quantum-inspired Evolutionary Algorithm (QEA) to reduce the searching process for finding the optimal phase factors
2011	Lingyin Wang and Ju Liu [75]	Combining Grouping Phase Weighting (GPW) and Recursive Phase Weighting (RPW) methods to reduce the complexity

Table 2.6: Major contribution to PTS based PAPR reduction in OFDM

Year	Author(s)	Contribution
2012	Hojjat Salehinejad and Siamak Talebi [17]	PAPR reduction based on novel global harmony search (NGHS) with PTS
2013	Xiangyu Yu, Shuai Li, Zhu Cong Zhu and Tao Zhang [77]	Modified ABC-PTS (artificial bee colony-partial transmit sequence) for PAPR reduction
2014	Li Li, Daiming Qu and Tao Jiang [79]	Joint decoding scheme to recover low-density parity-check (LDPC) codeword for PTS phase factors with low PAPR
2015	Wei Xiao, Honggui Deng, Fangqing Jiang, Kaicheng Zhu and Linzi Yin [80]	PTS technique based on the combination of a genetic algorithm (GA) and a hill-climbing algorithm (GH-PTS) to solve the problem of high PAPR

2.7.2 Recovering information without transmitting side information (SI)

In 2000, L. J. Cimini and N. R. Sollenberger [81] proposed a marking algorithm to reduce PAPR and detection of marking algorithm procedure to recover the data without transmission of side information at the receiver side. The BER performance of this algorithm showed improvement by increasing number of tones per sub-block. Another algorithm that inserts information into PTS-OFDM system without affecting the reduced PAPR and improves BER performance was proposed by A.D.S. Jayalath and C.Tellambura, 2003 [82]. This algorithm was a modified form of [81]. Seon-Ae Kim and Heung-Gyoon Ryu proposed a method that achieves a PAPR same as conventional PTS scheme and recovered side information without transmitting phase factors in 2006 [83]. In this method, the phase of reference symbols was used to give information about rotation factors at the receiver side. In the year 2011, L.Yang et al., [84] proposed a PTS method that detects OFDM symbols without sending the side information. The main principle of this detection scheme was to generate the required signals through circularly shifting of each sub-block sequence in the time domain and combining them in a recursive manner. So, by utilizing the diversity of phase constellation for different required signals, the detector recovered the original signal. The BER performance of the proposed scheme was similar to the conventional-PTS with perfect side information.

2.7.3 Combined method of PTS with other techniques

Houshou Chen and Hsinying Liang proposed a combined method of PTS and binary Reed-Muller (RM) codes for reducing PAPR and correcting errors in 2007 [85]. Reed-Muller code is separated into two subcodes. The scrambling subcode was used for reducing PAPR whereas the correcting subcode is used for encoding information bits. OFDM sub-carriers were partitioned into different sub-blocks according to natural and cyclic ordering. The achieved numerical and simulation results showed that cyclic order provided better PAPR performance than natural ordering. In 2008, Josef Urban and Roman Marsalek [39] proposed a combined technique of PTS and clipping and filtering. PTS was applied before the IFFT operation, and Clipping and Filtering are used after the IFFT operation. Clipping and Filtering with bounded distortion reduce complexity. The obtained result of the proposed method shows better PAPR and BER than each scheme. The year 2010 remarked two main contributions in the field of combined PTS methods. Pooria Varahram, Wisam F. Al Azzo, and Borhanuddin Mohd Ali [52] proposed a combined method that decreases the computational complexity of PTS. The proposed method was combination of the Dummy Sequence Insertion (DSI) and PTS.

As a comparison to the conventional PTS, this method had 0.5 dB lower PAPR for same CCDF and also reduces the requirement of several IFFT operations. In 2010 itself, Abolfazl Ghassemi and T. Aaron Gulliver [86] proposed a technique that employs error correcting codes (ECCs) to the partitioned sub-blocks of PTS. The application of ECCs reduces the sub-carriers that repeat within the sub-blocks. This technique utilizes the periodic auto-correlation function of the vectors in the partitioned sub-blocks. This achieves the PAPR as to the conventional PTS as well as significantly reduces the computational complexity.

2.8 Summary

In this chapter, a literature review on PAPR problem in OFDM system was presented. The chapter explains the occurrence of high PAPR in this system including its definition and its measurement parameters as well as the consequences of a high PAPR in amplifier. It also provides an overview of different PAPR reduction techniques. PTS with low complexity for searching phase factor needs efficient optimization methods that should be distortion-less techniques. In spite of good performance than other methods, complexity is a challenging issue of these optimization techniques. From the literature survey of PTS, it can be concluded that complexity arises mainly due to the selection of the weighting phase factors, IFFT operations and transmission of bits of side information. The literature survey of current research scenario on the PTS method for reducing PAPR with less complexity regarding the selection of phase factors, recovering the information without transmitting side information and hybrid combine method of PTS with others scheme have been presented. Literature surveys on different optimization methods for reducing PAPR have been carried out. So, we are mainly concerned with developing an optimization scheme based PTS that reduces the PAPR considerably using only a few numbers of sub-blocks.

CHAPTER **3**

Firefly assisted PTS (FF-PTS) for PAPR Reduction in OFDM

" No problem can be solved from the same level of consiousness that created it".

-Albert Einstein

Contents

3.1 Introduction

Bio-inspired algorithms are gaining popularity in different fields of research. They have the potential as an alternate technique to deal with different optimization problems and non-linear optimization constraint problem [87]. Such algorithms are based on natural biological phenomenon to provide a global optimal solution. These techniques are population-based nature inspired algorithms where, a large population of individual solution is randomly initialized. The quality of each solution is then estimated using a fitness function. After this process, a selection procedure is applied to form a new population. The searching process is biased towards better individuals to increase their chances of being included in the new population. The process is repeated until convergence criteria are met.

The Firefly (FF) algorithm is considered as a favorable optimization tool due to the effect of the attractiveness function that is unique to the firefly behavior. This algorithm not only includes a self-improving process within the current space, but it also includes the improvement of its space from the previous stages. The FF algorithm is seen to be very robust in solving non-linear optimization problems as presented in literature [88–91]. Also, the parameters in FF-PTS algorithm can be tuned to control the randomness as iterations proceed so that convergence can also be sped up by optimizing these parameters. These advantages make it flexible to deal with the different combinatorial optimization problems. In this chapter, we propose a swarm intelligence algorithm for phase optimization in PTS technique. The algorithm based on Firefly based PTS (FF-PTS) scheme, which can reduce the PAPR significantly. The proposed scheme searches an optimum combination of phase vectors and offers excellent performance in terms of PAPR reduction. Simulation result show that the proposed FF-PTS phase optimization technique can achieve superior PAPR reduction performance as compared to conventional

PTS scheme requiring lower computational complexity for large number of sub-blocks compared to conventional PTS techniques.

3.2 Firefly Algorithm

Fireflies are the most charismatic species among insects, and their spectacular display have inspired poets, writers and scientists. Today more than 2000 species of firefly exist, Flashing of the fireflies can be seen in the summer sky in the tropical and temperate regions with warm weather and most active in the nights [92]. Fireflies produce short rhythmic patterns of flashing lights and these patterns of flashes are unique from species to species, and the flashing light is produced by a bio-luminescence process. Moreover, this flashing produced is understood to attract their partners; the first signallers are flying males who try to attract the females on the ground. In response females also emit flashing lights and move towards the brightest firefly. However the flashing lights obey certain physical rules, the light intensity I decrease with the increase of distance r according to the term $I \propto 1/r^2$. Also, the flashing is produced for communication purpose among each other and it also to attracts prey. The flashing behavior has been a topic of discussion among scientists [92].

The Firefly Algorithm (FF) is a new nature-inspired algorithm developed by Xin-She-Yang in the year 2009 [66], based on the flashing patterns and behavior of fireflies. The flashing signifies the signal to attract other fireflies, where an objective function associated with the flashing light or the light intensity helps the fireflies to move to brighter and more attractive locations to achieve an optimal solution [91,93,94]. A comprehensive review of Firefly algorithms has been analyzed by Fister et al [95].

3.2.1 Structure of Firefly Algorithm

The firefly algorithm has three idealized rules or assumptions that have been developed to define the characteristics of fireflies [66]:

- All fireflies are unisex and they move towards the more attractive and brighter one irrespective of their sex.
- The level of attraction of a firefly is proportional to the brightness that reduces with the increase in the distance between two fireflies since air absorbs the light. If there is no other attractive firefly than a particular one, then they move randomly.
- The brightness or light intensity is determined by the value of the objective function of a given problem and it is proportional to the light intensity for a maximization problem.

The flashing light can be formulated in such a way that it is associated with the objective function to be optimized.

3.2.2 Characteristics of Firefly Algorithm

Proper designing of the firefly algorithm for any engineering application can be defined on two important issues: the variation of the light intensity and the formulation of the attractiveness [87]. For simplicity, it is assumed that the attractiveness of a firefly is determined by its brightness, which in turn is associated with the encoded objective function.

(a) **Attractiveness:** In the FF algorithm, the brightness I of a firefly at a particular location x can be chosen as $I(x) \propto f(x)$. However, the attractiveness β is relative and judged by the other fireflies. Thus, it varies with the distance r_{ij} between the firefly i and j. The light intensity $I(r)$ varies according to the inverse square law $I(r) = I_s/r^2$, where I_s is the intensity at the source. In order to avoid the singularity at $r = 0$ in the expression $I(r) = I_s/r^2$, the combined effect of both the inverse square law and absorption can be approximated by the function of the distance r between any two fireflies using the following Gaussian form:

$$I(\mathrm{r}) = I_0 e^{-\gamma r^2}, \tag{3.1}$$

where I_0 is the original light intensity. Sometimes, we may need a function which decreases monotonically at a slower rate. In this case, we can use the following approximation:

$$I(r) = \frac{I_0}{1+\gamma r^2} \tag{3.2}$$

At a shorter distance, the above two forms are essentially the same. This is because the series expansions about $r = 0$

$$e^{-\gamma r^2} \approx 1 - \gamma r^2 + \frac{1}{2}\gamma^2 r^4 + \ldots, \qquad \frac{1}{1+\gamma r^2} \approx 1 - \gamma r^2 + \gamma^2 r^4 + \ldots \tag{3.3}$$

are equivalent to each other up to the order of $O(r^3)$.

As a firefly's attractiveness is proportional to the light intensity seen by adjacent fireflies, we can now define the attractiveness β of a firefly by

$$\beta(\mathrm{r}) = \beta_0 e^{-\gamma r^2} \tag{3.4}$$

where, β_0 denotes the maximum attractiveness (at $r = 0$) and γ is the light absorption coefficient, which controls the decrease of the light intensity. As it is often faster to calculate $1/(1 + r^2)$ than an exponential function, the above function, if necessary, can conveniently be replaced by $\beta = \frac{\beta_0}{1+\gamma r^2}$. In the implementation, the actual form of attractiveness function $\beta(r)$ of the fireflies varies according to the relation :

$$\beta(\mathrm{r}) = \beta_0 e^{-\gamma r^m}, m \geq 1 \tag{3.5}$$

(b) **Distance:** The distance between two fireflies i and j at positions p_i and p_j can be defined by the euclidean distance in multidimensional space and calculated as:

$$r_{ij} = \|p_i - p_j\| = \sqrt{\sum_{k=1}^{d} (p_{i,k} - p_{j,k})^2} \tag{3.6}$$

where $p_{i,k}$ is the k-th component of the spatial coordinate p_i of i-th firefly and d denotes the dimensionality.

(c) **Movement:** The movement of a firefly i is determined by the following form:

$$p_i' = p_i + \beta_0 e^{-\gamma r_{ij}^2} (p_j - p_i) + \alpha \left(rand - \frac{1}{2} \right) \tag{3.7}$$

where the first term p_i is the current position of a firefly i, the second term denotes a firefly's attractiveness and the last term is used for the random movement and *rand* is a random number, uniformly distributed in the range (0,1).

The algorithmic parameters are fixed by trial and error for best performance. The attractiveness co-efficient β_0 (between zero and 1, default = 0.2) and randomization parameter α (between zero and 1, default = 0.25) has been considered in the simulation. As per FF algorithm, the randomization parameter and β_0 should be less than 1 and it has been maintained in simulations [66, 93, 103]. In practice the light absorption coefficient γ varies from 0.1 to 10. This parameter describes the variation of the attractiveness and its value controls the convergence speed of the firefly algorithm.

3.3 PAPR minimization using Firefly Algorithm

This section describes the process of phase vector optimization in the PTS technique using firefly algorithm. To process OFDM signals with an aim to achieve minimum PAPR, a suboptimal combinatorial method based on the Firefly algorithm (FF) is presented here. This design aims to solve the optimization problem of the PTS technique. The FF-PTS algorithm can provide superior PAPR performance as compared to the conventional IPTS algorithm.
The minimum PAPR for the PTS method can be considered as an optimization problem:
Where the target is to minimize the function

$$f(b) = \frac{\max\left[|x'(b)|^2\right]}{E\left[|x'(b)|^2\right]} \tag{3.8}$$

subject to

$$b \in \left\{e^{j\phi_m}\right\}^M \tag{3.9}$$

where $\phi_m \in \left\{\frac{2\pi k}{W} \,|k = 0, 1, ..., W-1\right\}$; W is the set of allowed phase rotation factors.

The Analogy between PTS parameters and FF algorithm parameters is presented using the Table 3.1. The algorithm explains in terms of PTS optimization and maps the PTS parameters to FF parameters. The flowchart for the FF algorithm is presented in Figure 3.1. The steps used to optimize the phase vectors in the proposed FF-PTS algorithm are as follows:

- **Parameter initialization:**
  In the FF-PTS algorithm, attractive (brighter) firefly position represents a phase vector $b_i = [b_{i,1}, b_{i,2}, ...b_{i,M}]$, where $i = 1, 2...G_n$, where G_n denotes the size of a randomly distributed initial population.

Table 3.1: Analogy of Firefly optimization process with PTS

Firefly Analogy	**PTS Analogy**
Aim= Selection of brightest firefly	Aim= Optimize the objective function
Firefly	Phase Vector
Population	No of Solution
Generation	Iteration
Random attractive firefly	Random solution
while $(I_j > I_i)$	Current Sol > Previous Sol
If true, next firefly is selected and updated	Next is the solution
If false, current firefly is updated	Current is the solution
Repeat this up to $t < MaxGen$	Repeat this up to best solution
Best objective firefly after all iterations	Best solution after all iterations

- **Light intensity formulation of fireflies:**

  Initially the set of possible phase factor combinations is identified as the available population of fireflies G_n. Light intensity I is formulated, so that it is associated with the objective function $f(b)$. Each row in the matrix is a set of solutions by evaluating $f(b)$ between lower and upper bound values which results in randomly populating the solutions for each structure ($i = 1, 2, ...G_n$), the objective function $f(b)$ is evaluated, which takes the value from various combinations of b_i.

- **New solution construction:**

  The movement of a firefly b_i^{min} attracted to another more attractive (brighter) firefly b_i^{max} is calculated by following relationship:

$$b_i' = b_i^{min} + \beta(r)\left(b_i^{max} - b_i^{min}\right) + \alpha\left(rand - \frac{1}{2}\right) \tag{3.10}$$

where the first term b_i^{min} is the current position of a firefly i, the second term denotes a firefly's attractiveness and the last term is used for the random

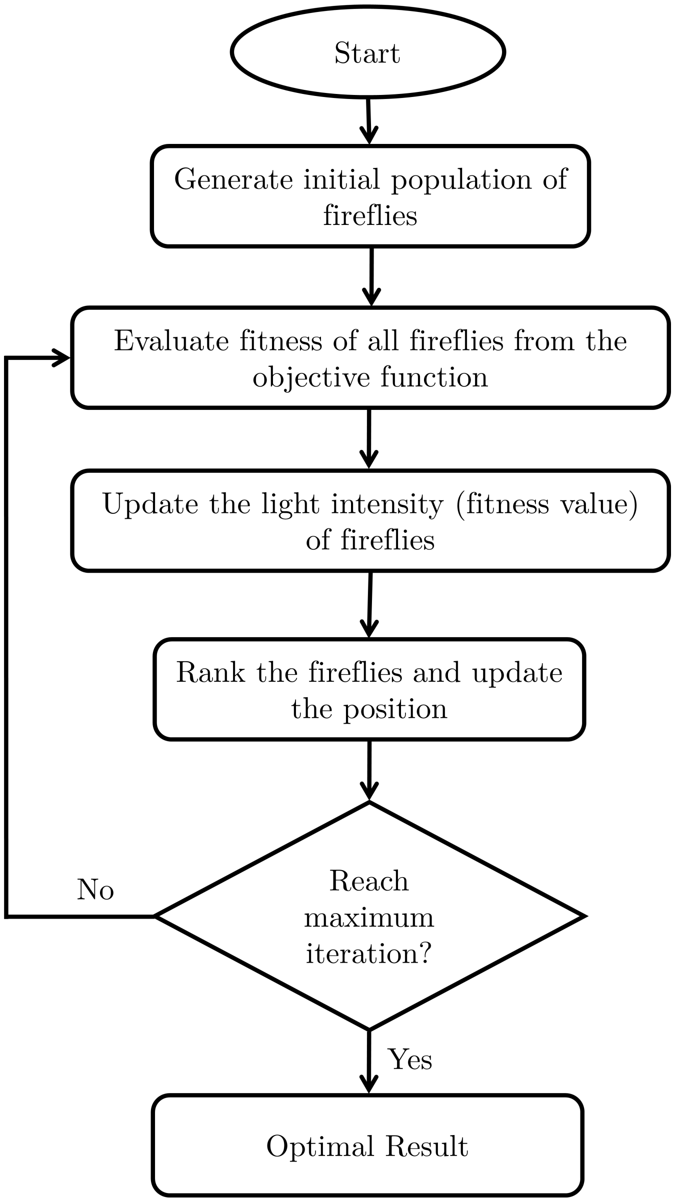


Figure 3.1: Flowchart for Firefly Algorithm

movement and *rand* is a random number, uniformly distributed in the range (0,1). Here, β is the attractiveness co-efficient calculated by (3.4) and r is

Algorithm 1 Firefly Algorithm for PAPR reduction (FF-PTS)

Define the fitness function $f(b), b \in \left\{e^{j\phi_m}\right\}^M$
Set the input parameter of the firefly algorithm such as:
Maximum generation (Max Generation) (number of iteration cycles);
Population size (G_n) (number of fireflies);
Number of variables (d) (the d-dimensional search space);
The light absorption co-efficient (γ) (between zero and infinity, *default* $= 1$);
The attractiveness co-efficient (β_0) (between zero and 1, *default* $= 0.2$);
The randomization parameter (α) (between zero and 1, *default* $= 0.25$);
for $i = 1 : G_n$
    $b_i = rand(b_{i,1}, b_{i,2}, \ldots b_{i,M})$, where $i = 1, 2 \ldots G_n$; Create a set of random solutions to the problem
    $f(b_i)$; Calculate the fitness function
end for
Sort the solutions from best to worst (brightest to dimmest)
for counter= 1 to *Max Generation*
    for $min = 1 : G_n$
        for $max = 1 : G_n$
            $r_0 = \|b_i^{min} - b_i^{max}\| = \sqrt{\sum_{k=1}^{d} \left(b_{i,k}^{min} - b_{i,k}^{max}\right)^2}$
            if $(I_j > I_i)$ **then**,
                $b_i' = b_i^{min} + \beta_0 e^{-\gamma r_0^2} \left(b_i^{max} - b_i^{min}\right) + \alpha \left(rand - \frac{1}{2}\right)$
            end if
        end for(max)
    end for(min)
end for
$f(b_i)$; Calculate the fitness function for the new firefly's locations.
Sort the solutions from best to worst (brightest to dimmest).

the distance between two fireflies b_i^{min} and b_i^{max} and will be calculated by:

$$r_0 = \left\|b_i^{min} - b_i^{max}\right\| = \sqrt{\sum_{k=1}^{d} \left(b_{i,k}^{min} - b_{i,k}^{max}\right)^2} \tag{3.11}$$

where $b_{i,k}$ is the k-th component of the spatial coordinate b_i of i-th firefly and d denotes the dimensionality.

A random walk process defined by a vector of random numbers drawn from a uniform distribution selects a new phase value with the value from the combinations of phase vectors W. The discretization of b'_i, i.e. selecting the closed solution from the possible values of W will be explained by the following expression:

$$bc_{i+1,m} = \exp\left(\frac{j2\pi\left[\frac{W\angle(b'_{i,m})}{2\pi}\right]}{W}\right); m \in 1, ...M$$

Where [.] denotes rounding to the nearest integer value. This generates candidates bc_{i+1} for iterations $i+1$ to ranking against the current solutions, so that weakest can be removed.

The b'_i values are as follows:

$$b'_i = \begin{cases} \{\pm 1\}, & if\ W = 2 \\ \{\pm 1, \pm j\}, & if\ W = 4 \end{cases} \tag{3.12}$$

The process is repeated with each iteration until the worst solution is replaced by new phase factor values.

- **New light intensity update:**

  The generation of top phase factor values (brighter firefly) is slightly different from the lower one, depending upon the light intensity of firefly. First phase factor with its PAPR value is compared with the PAPR of the randomly chosen phase factor from the available phase factor combinations. If the PAPR value is less than the existing PAPR, then it replaces the current value. In case both the new and present values are same, the random walk step is applied to choose the new phase factor value randomly and then it is updated by following relationship:

$$b'_i = b_i^{min} + \beta_0 e^{-\gamma r_0^2}\left(b_i^{max} - b_i^{min}\right) + \alpha\left(rand - \frac{1}{2}\right) \tag{3.13}$$

where b_i^{max} and b_i^{min} are two distinct vectors picked up randomly from the current population and *rand* is a random number, uniformly distributed in the range (0,1) and $\alpha \in (0,1)$. Under this scheme, target solutions are not always attracted towards the same best position found so far by the entire population. This feature helps avoid premature convergence at local optima. All the phase factors contributing to generating the new phase factor combination via random walk process are used. The phase factor with the best PAPR values are placed for the next generation.

- **Stopping criterion:**
  The algorithm is repeated until the total number of function iterations K is reached and according to the ranking of fireflies, the top phase factor values are compared with the new phase factor values. The optimum phase factor combination producing the smallest PAPR value, on completion of K iterations is selected.

3.4 Simulation Results and Discussions

Simulation studies were conducted to evaluate the performance of the FF-PTS algorithm for PAPR reduction in OFDM signals. To generate the CCDF of the PAPR, 10,000 OFDM symbols with 16-QAM modulation were first generated from random input data set b. Following this, the transmitted signal was oversampled by a factor of 4 for accurate PAPR computation. The performance of the FF-PTS has been evaluated over a variety of conditions.

3.4.1 Effect of algorithmic parameter variation on PAPR

It was observed that the FF algorithm has three control parameters. The G_n denotes the number of sample solutions, also termed as population size, α is a scale factor and γ the absorption coefficient. One of the important aspects is to determine the convergence speed of the iterative process. The parameters α and γ, are stated to be related to the convergence speed and the priori information reliability respectively, are more influential to the algorithms performance i.e.convergence. The convergence speed of the FF-PTS method is slow at initial stage due to lack of candidate samples to produce better samples in the next iteration [66]. At the same time, the convergence speed of the FF-PTS algorithm is towards the optimal solution of phase factor combination and decreases with increase in population size [96]. Hence, it is important to select α and γ appropriately to achieve good PAPR performance. All of these parameters affect the speed and robustness of the search space.

3.4.1.1 Variation in α

To evaluate the effect of α on PAPR reduction using the FF algorithm, simulation were conducted as stated in the previous section. The results of PAPR in the form of a CCDF plotted against different PAPR values are presented in Figure 3.2. The results shows the PAPR performance comparison with increase in α for the FF-PTS technique. It is seen that the FF-PTS algorithm converges close to superior solution ability for better solution. The results shows that the PAPR performance improves with an increase in α. When α is between 0.3 to 1 (0.3, 0.5, 0.8, 1 in the simulation), $P_r(PAPR > PAPR_0)$ terminates before reaching the value 10^{-3}. Considering that the number of OFDM symbol is 10,000, the number of samples detected with requisite P_r is zero. This occurs when $PAPR > PAPR_0$ for only one sample. In the instant 4 cases, none of the 10,000 samples have a $PAPR > PAPR_0$. It is possible to extend the simulations by order of 10 times with 1,00,000 samples. This results in very long simulation time to the tune of tens of hours per simulation.

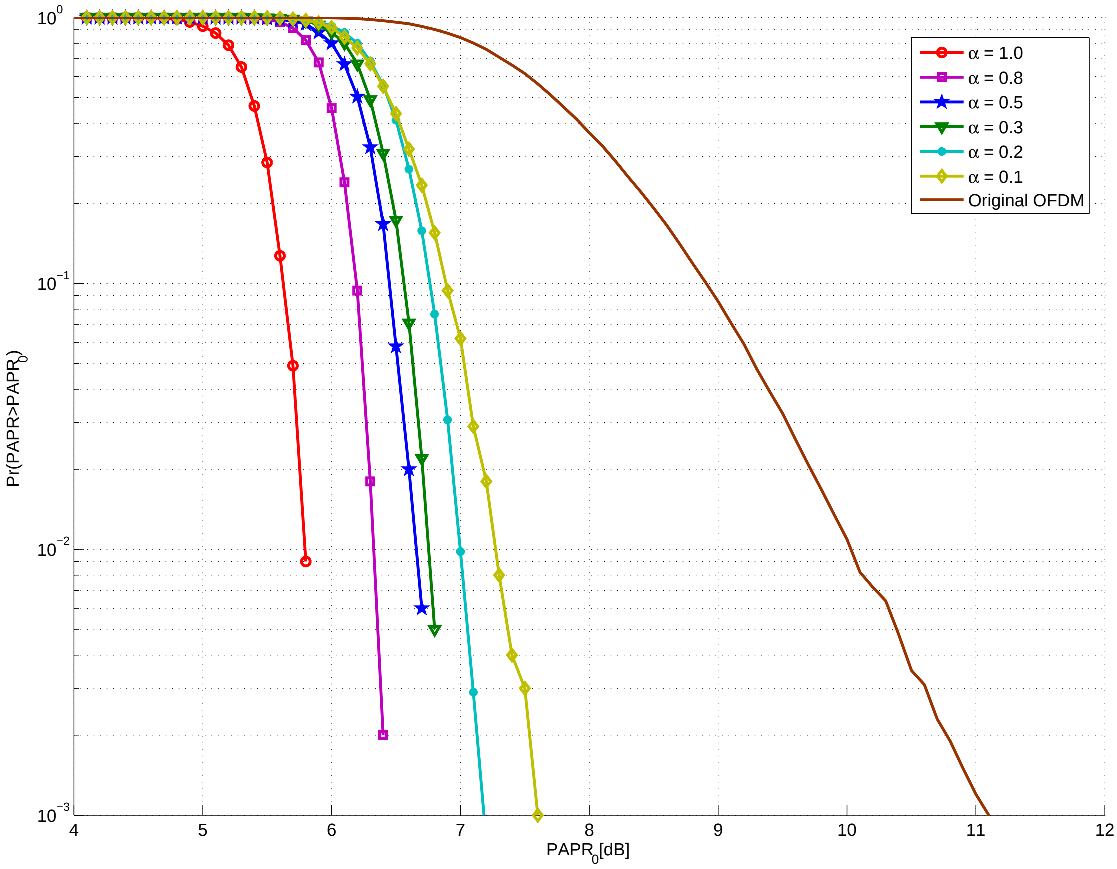


Figure 3.2: PAPR performance of FF-PTS algorithm with variation in α for M =16, N = 256, G_n = 10 and γ =1.0

By adjusting parameter γ and α, the FF-PTS algorithm is seen to provide superior performance compared to conventional PTS algorithm. The algorithm is also able to find better global optima as well as local optima simultaneously and efficiently [97]. This requires careful selection of α considering number of samples available for training.

3.4.1.2 Variation in γ

The choice of γ which is typically regarded as only a fine tuning parameter is initially recommended to be $0.1 \leq \gamma \leq 1.2$ [93]. In this test, we suggested that a good initial choice of α is 0.2 or 0.3 as per discussion in previous sub-section

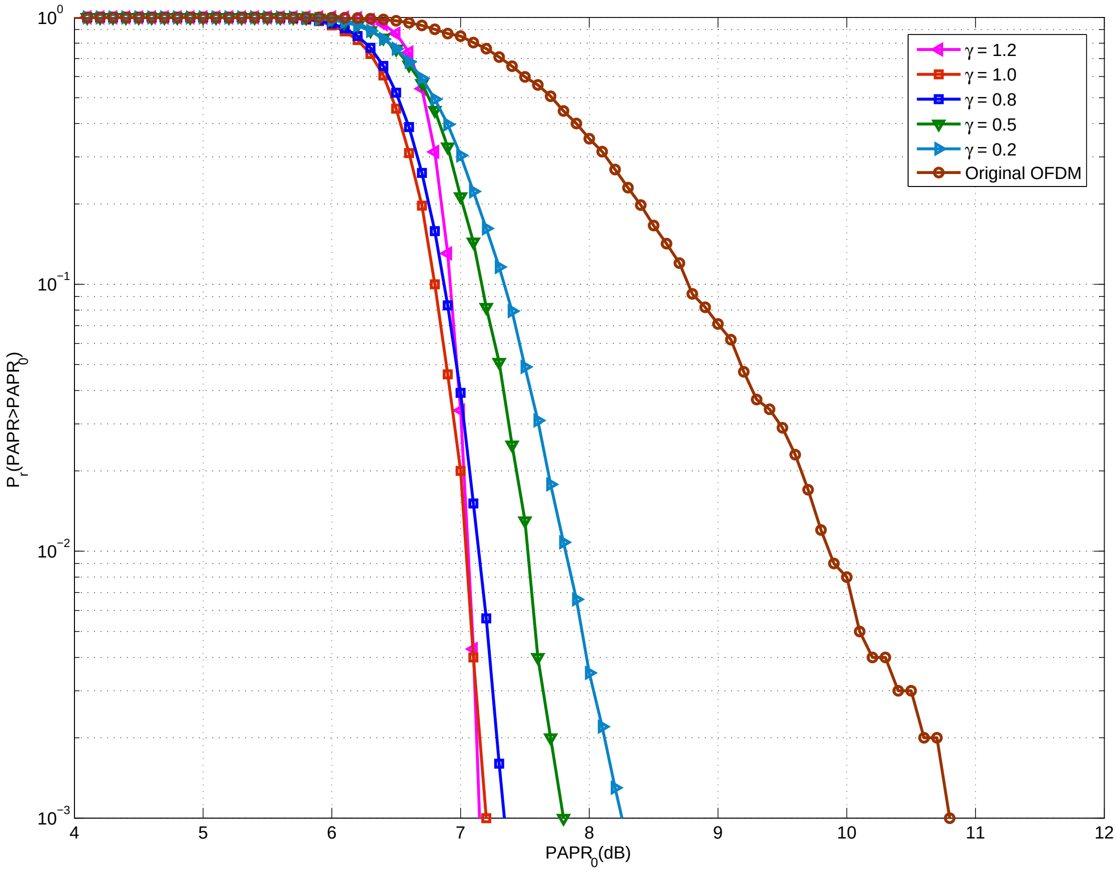


Figure 3.3: PAPR performance of FF-PTS algorithm with variation in γ for M=16, N= 256, α =0.25 and G_n =10

with G_n = 10 and γ can be set to 0.8 or 1.2. Figure 3.3 presents the results of PAPR in the form of CCDF against different values of γ. The results show the range of γ from 0.8 to 1.2 provides good trade-off between convergence speed and performance. So, the value of γ=1 has been considered for further simulation studies. According to the simulation results, the selected strategies and parameter settings exhibit distinct advantages. Thus, a change in the FF parameter changes the effectiveness of the algorithm and tuning of these parameters highly affects the performance of FF. Furthermore, linearly increasing and decreasing α during iteration with γ proportional to various combinations of maximum values of the objectives at different iterations. The value of the control parameters for different conditions provided in this section can guide the users to optimally use this algorithm for further designs. From the two figures, it can be easily found that α=0.25 and γ=1.0 is a good choice in terms of the performance.

Based on the above analysis, the simulation parameters were fixed for an extensive study and shown in Table 3.2 for FF-PTS algorithm. The basic steps of FF-PTS technique can be summarized by the pseudo code shown in Algorithm 1. The search complexity of FF-PTS algorithm is equal to ${G_n}^2K$, where G_n represents the population of fireflies and K is the total number of function iterations [98].

Table 3.2: FF-PTS Simulation Parameters

Simulation Parameters	**Type/Value**
Number of sub-carriers (N)	128, 256, 512
Number of sub-blocks (M)	4, 8, 16
OFDM Blocks	10,000
Oversampling Factor (L)	4
Bits per symbol (b)	4
Phase rotation factors (W)	$\{+1, -1\}$
Dimensions of fireflies (d)	2
Population of fireflies (G_n)	10
Randomization parameter (α)	0.25
Firefly attractiveness co-efficient (β_0)	0.20
Absorption coefficient (γ)	1
Constellation Size	16-QAM
No. of iterations (K)	10, 20, 50, 100

3.4.1.3 Variation in number of iterations K

Figure 3.4 illustrates the CCDF vs PAPR performance of 16-QAM OFDM-PTS system as a function of iterations K. The system considers the number of sub-carriers (N)= 256, number of sub-blocks (M)= 4 and phase factor (W)=2. When the number of iterations is 5, then PAPR achieved by FF-PTS is 8 dB. After increasing the iterations from 5 to 10, it gives a performance improvement of 0.3 dB.

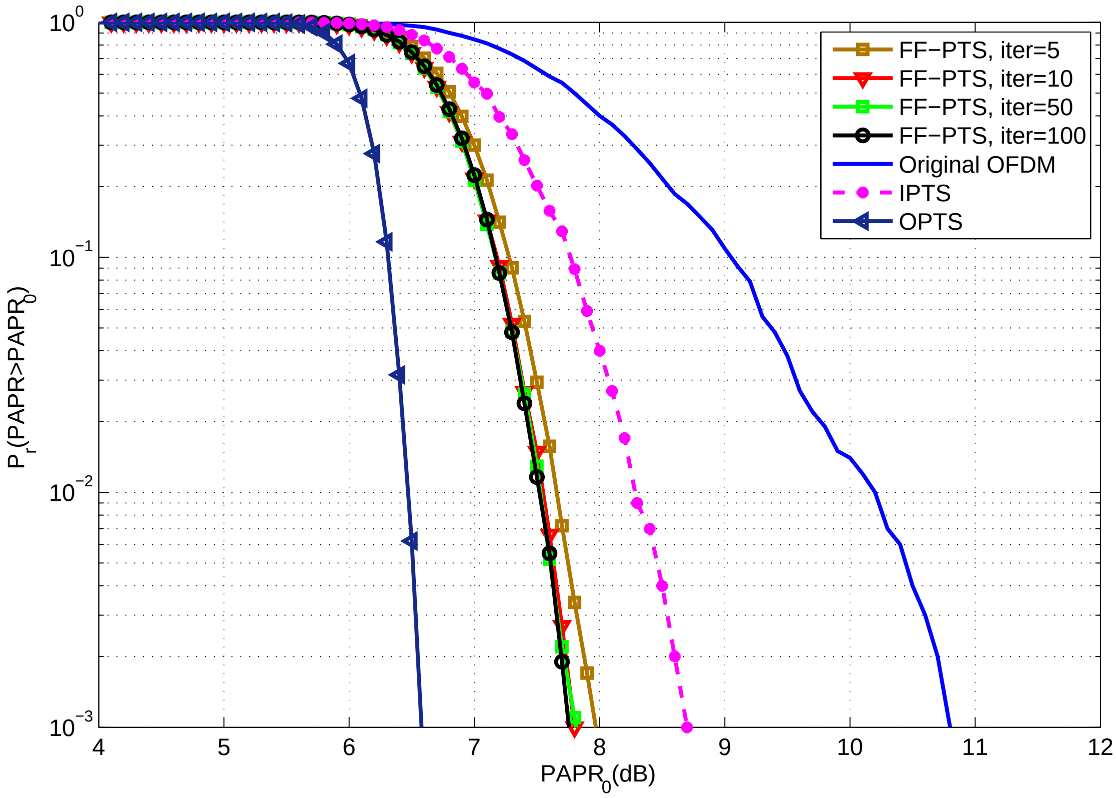


Figure 3.4: CCDF vs PAPR performance of 16-QAM FF-PTS system for K=5, 10, 50, 100 iterations, when N= 256, M=8, W=2, G_n=10

Any further increase in the number of iterations does not provide an observable gain. As K increases, the FF-PTS technique provides almost same PAPR performance but with much higher computational complexity. Due to large number of iterations, processing time becomes longer, and the number of function evaluations leading to computation complexity enhancement. The PAPR performance saturates close to 7.75dB beyond 20 iterations. Considering this, further simulations and result comparison were carried out with 10 iterations.

Figure 3.5 shows the evolution curve of FF-PTS technique, which represents graph between mean of best cost function values i.e. PAPR and iteration numbers. It is well known that increasing the number of iterations causes increment of searching complexity of the phase factor too. So, from descriptions, we can see

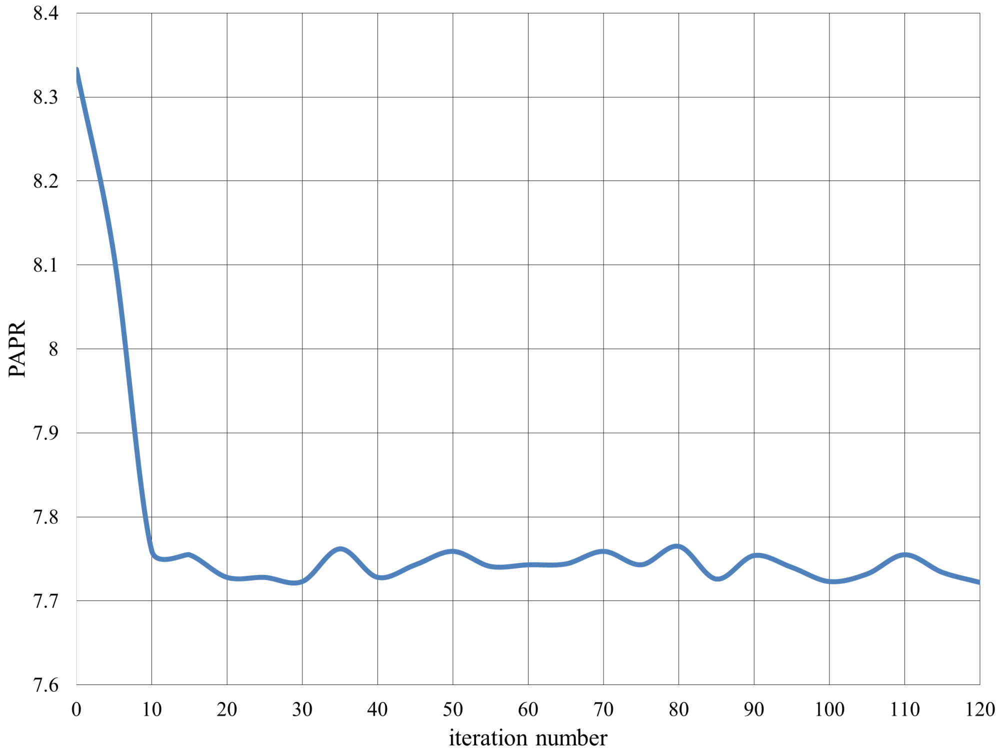


Figure 3.5: Evolution curve of FF-PTS algorithm for population size G_n=10

that the FF-PTS is a useful technique for reducing the PAPR and has very little improvement in increasing the number of iterations from 10 to 100.Hence K =10 for FF-PTS scheme has been used further, and it provides a good tradeoff between the PAPR performance and computational complexity.

3.4.1.4 Variation in population size G_n

Following the effect of iterations, effect of population size G_n was investigated. Figure 3.6 presents some results of the CCDF of the PAPR for FF-PTS technique for various populations of the fireflies G_n. Here, N=256 sub-carriers with M=8 sub-blocks employing random partitions are used along with phase weight factor W=2. For population G_n =40, it can be seen that the FF-PTS technique provides improved PAPR performance, with CCDF requirements of 10^{-3}. It can also be

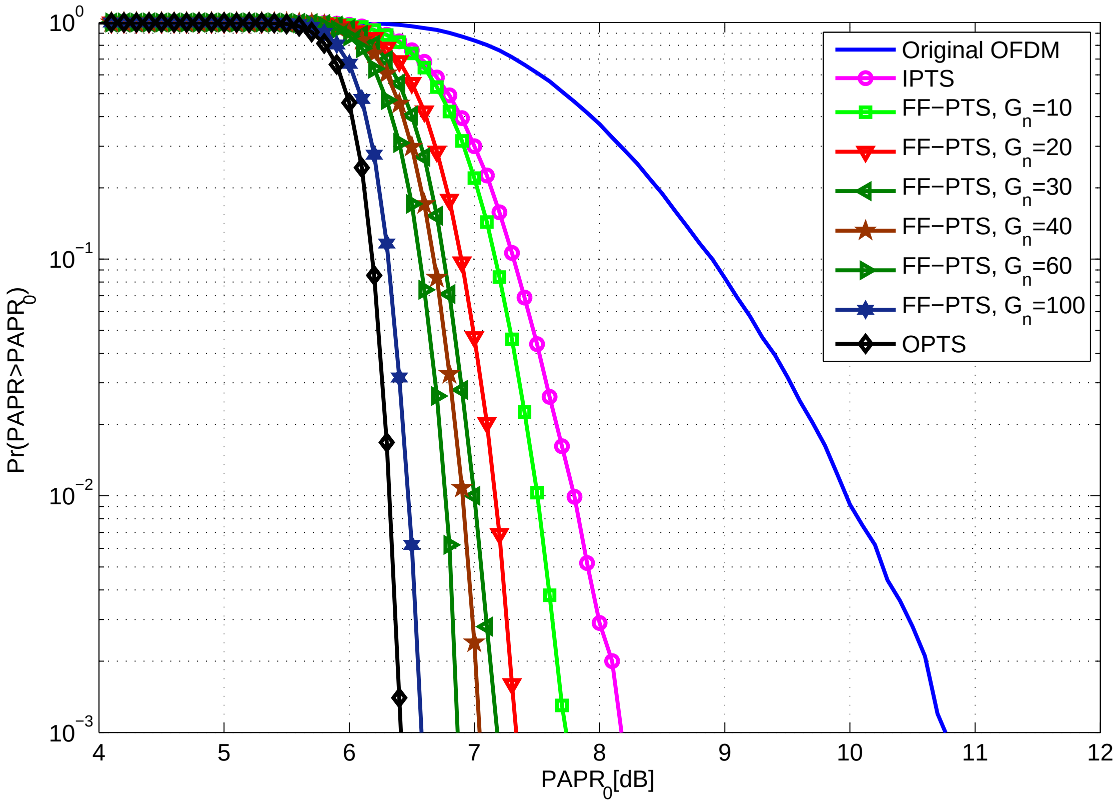


Figure 3.6: CCDF vs PAPR performance of 16-QAM FF-PTS system for firefly population G_n=10, 20, 30, 40, 60, 100 when N= 256, M=8, W=2, K=10

seen that the PAPR performance gradually improves by increasing the population size due to the wide choice of phase weighting factor. As the firefly population size increases, the CCDF improves but the computational complexity also increases related to square of the population size G_n [98]. Considering minor performance gain with population G_n, an appropriate population number G_n =10 has been chosen for acceptable PAPR performance and complexity. When a large number of fireflies are used, the convergence of the algorithm can be achieved. Here, the initial location of G_n fireflies is distributed uniformly in the entire search space, and as the iterations K of the algorithm continues, fireflies converge to all the local optimum points. The global optima is achieved by comparing the best solution among all these possible combination of phase factors. By adjusting parameter γ and α, the FF-PTS algorithm is seen to outperform as compared to conventional PTS algorithm. It can also find the global optima as well as local optima simultaneously and efficiently.

3.4.2 PAPR performance analysis for OFDM system indices

Sensitivity of the algorithmic parameters were discussed in the previous subsection. Following this, the performance of FF-PTS has been evaluated for different number of parameters.

3.4.2.1 CCDF vs PAPR performance with variation in number of sub-blocks M

Figure 3.7 illustrates CCDF vs PAPR performance of 16-QAM FF-PTS system for M=4, 8 and 16 sub-blocks, when the number of sub-carriers (N)= 256 and phase factor (W)=2 . It can be seen that the PAPR of the original OFDM signal is around 11.1 dB with CCDF of 10^{-3}. On use of PTS and FF-PTS technique for M=4 sub-blocks, the PAPR reduces to 8.9 dB and 8.3 dB respectively. When M = 8 and 16 sub-blocks, it is seen that FF-PTS scheme provides reduced PAPR as compared to the IPTS technique. For M=8, the PAPR is 8.2 dB on applying IPTS and, after performing FF-PTS, the PAPR of OFDM signal is seen to be 7.8 dB result in 4dB. Similarly for M=16, the PAPR of PTS is around 7.6 dB, and when FF-PTS used, PAPR reduced to approximately 7.2 dB. Optimum PTS (OPTS) could not be supported for large number of sub-blocks due to high searching complexity and very long simulation time, hence IPTS results are presented here for comparative analysis. These simulation results indicate that the FF-PTS method provides 0.5 dB of PAPR performance improvement and performs better than the IPTS technique, when the number of sub-blocks varies from 4 to 16. Moreover, it can also be seen that the performance of the PAPR reduction becomes better

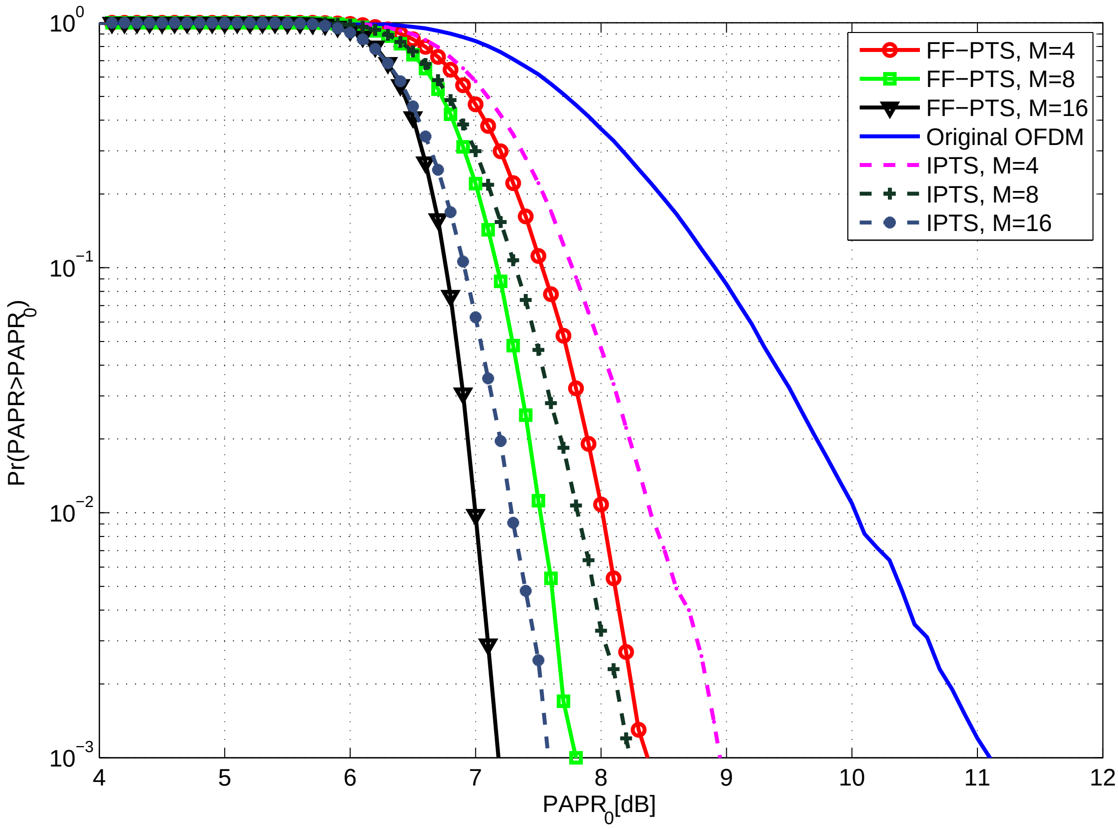


Figure 3.7: CCDF vs PAPR performance of 16-QAM OFDM-PTS system for M= 4, 8, 16 sub-blocks, when N= 256, W=2, G_n=10, K=10

as the number of sub-blocks and the set of phase weighting factors are increased. But, this is achieved at increased processing time.

3.4.2.2 CCDF vs PAPR performance with variation in number of sub-carriers N

Figure 3.8 presents simulation results of CCDF vs PAPR performance of 16-QAM OFDM system for N= 128, 256 and 512 sub-carriers, when M=8 and W=2. Simulation performance for original OFDM, IPTS and FF-PTS algorithm using different number of sub-carriers are presented here. It is seen from the CCDF plot that,the PAPR improves by increasing the numbers of sub-carriers due to the limited phase weighting factor. As the number of sub-carrier increases, the PAPR

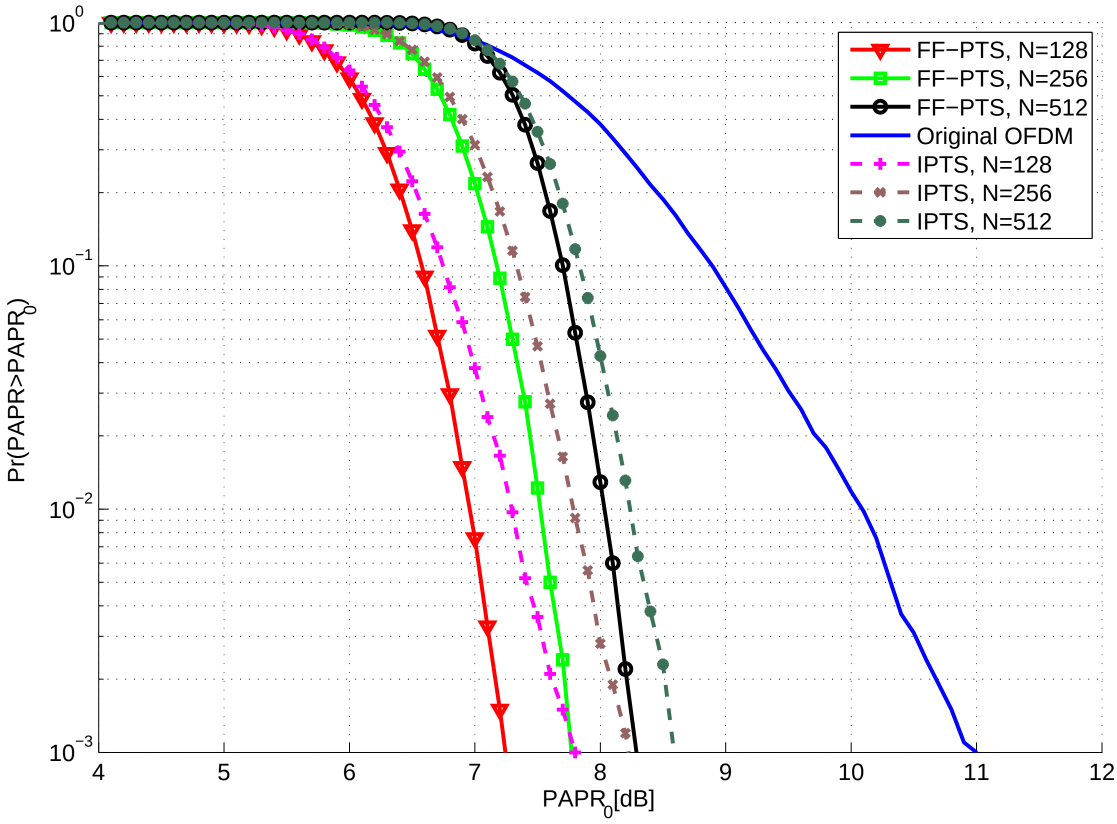


Figure 3.8: CCDF vs PAPR performance of 16-QAM OFDM-PTS system for N= 128, 256, 512 sub-carriers, when M=8, W=2, G_n=10, K=10

also improves. It is also seen, when N= 128, M= 8 and W=2, the PAPR of the IPTS scheme is approximately 7.8 dB, where as on applying FF-PTS, PAPR reduced to approximately 7.2 dB with CCDF of 10^{-3}. In continuation with this, when N= 256, M= 8 and W=2, after applying IPTS and FF-PTS, PAPR are observed to be 8.2 dB, 7.8 dB respectively with CCDF of 10^{-3}. However with N= 512 sub-carriers, the PAPR of the IPTS and FF-PTS are approximately 8.6 dB and 8.3 dB respectively. It is clear that a PAPR performance improvement of 0.5dB was provided by the FF-PTS method after increasing the sub-carriers from 128 to 512. So, it is observed that quantity improvement in PAPR are dependent on the number of sub-carriers used for OFDM generation, and the optimization

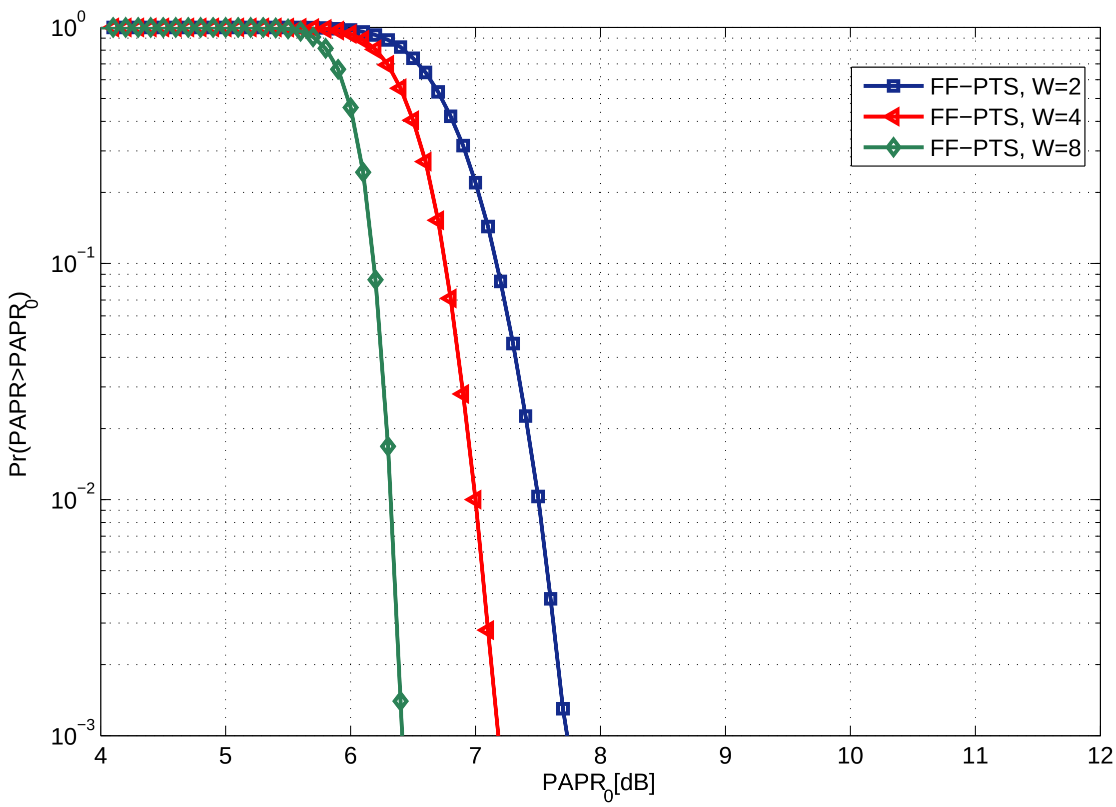


Figure 3.9: CCDF vs PAPR performance of FF-PTS system for W=2, 4 and 8, when N= 256, M=8,G_n=10 and K=10

algorithms provide improvement in PAPR performance in each case. From the above descriptions, we can see that FF- PTS is a effective technique for reducing the PAPR of OFDM system, even with the large number of sub-carriers.

3.4.2.3 Effect of variation in number of phase factors W

The effect of number of phase factors W taken was analyzed next. The results presented in Figure 3.9 compare the performance of FF-PTS technique for different values of phase factors. It implies that the performance of PAPR reduction is directly proportional to the factor of the number of phase weighing factor. As the number of sub-blocks and phase weigh factors increases, PAPR reduction could be improved. However, when the number of phase weighing factor is large one,

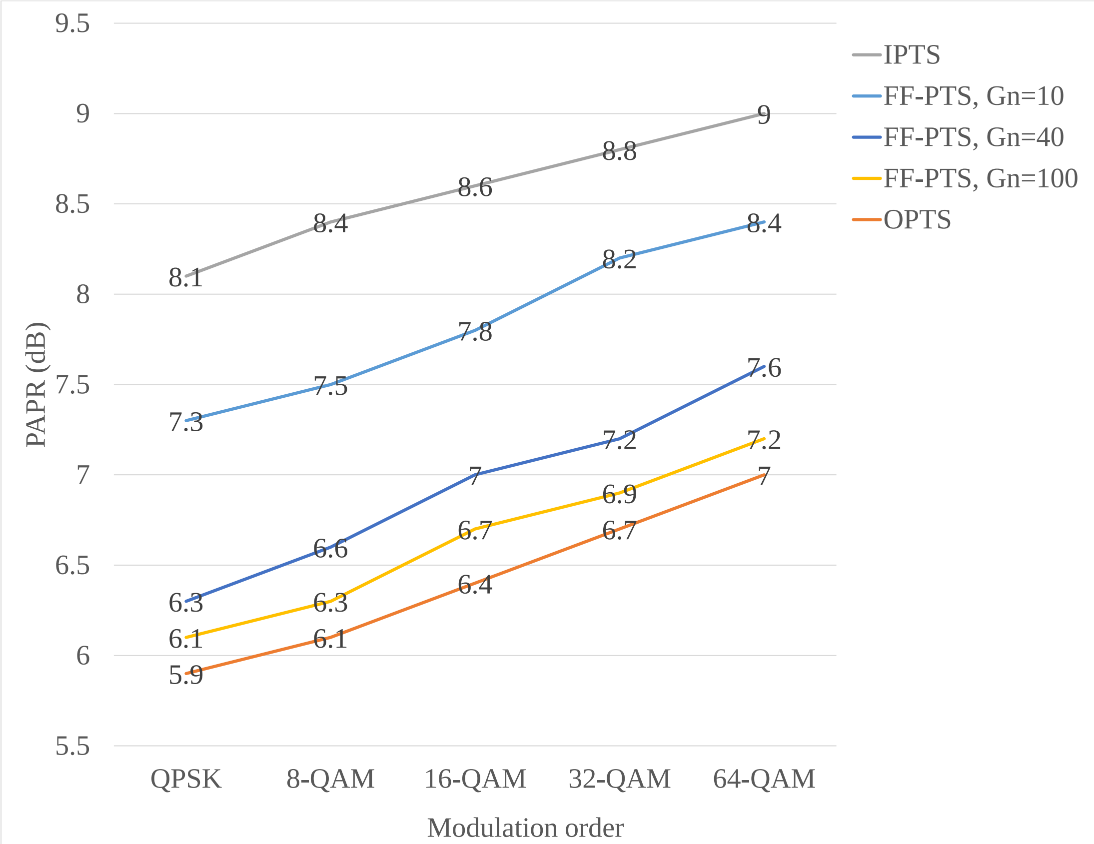


Figure 3.10: FF-PTS performance for different modulation formats

the number of parallel addition processor and number of phase weighing factor patterns needs a complex computation to find the optimum set of phase weighing factors and it leads to a heavy load for the system. So, due to the fact the number of phase factor W=2 has been considered for simulations in the thesis.

3.4.2.4 FF-PTS performance for different modulation formats

The FF-PTS algorithm was next analyzed for effect of modulation format on PAPR. Figure 3.10 presents the PAPR performance of FF-PTS scheme for different modulation orders like QPSK, 8-QAM, 16-QAM, 32-QAM and 64-QAM. Simulation parameters were considered as M=8 sub-blocks, N=256 sub-carriers,

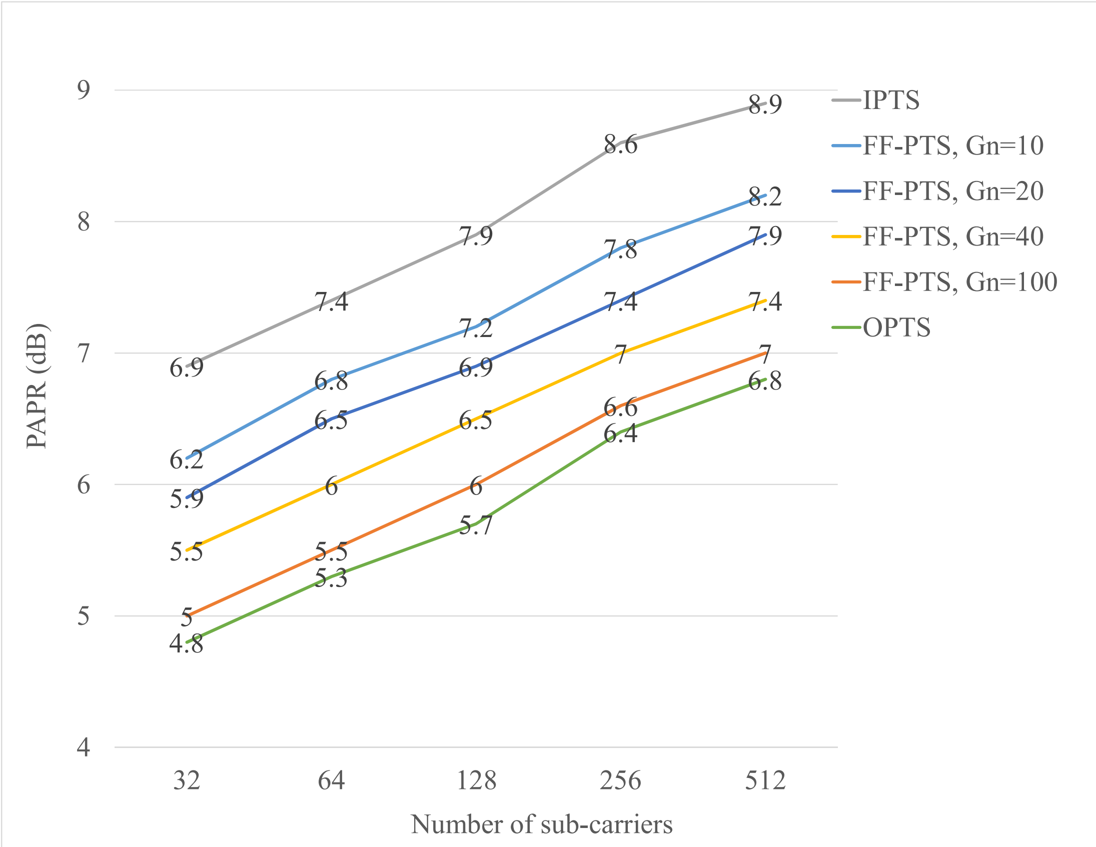


Figure 3.11: 16-QAM FF-PTS performance for different number of sub-carriers

W=2, K=10 iterations and α=0.25. The population size/ generations were considered from 10 to 100. It can be seen from results that FF-PTS provides linear performance degradation with increase in modulation order. This performance degradation is similar to performance degradation using OPTS and IPTS. At G_n=100, PAPR performance of FF-PTS technique is close to OPTS, but at the cost of very high complexity. So, a trade-off between PAPR performance and complexity calculation in terms of population size is required for implementation.

3.4.2.5 FF-PTS performance with varying number of sub-carriers

The effect of sub-carrier variation was analyzed next. The summarized results are presented in Figure 3.11. Here, the 16-QAM FF-PTS performance for different number of sub-carriers in the range 32 to 512, when M=8, W=2, K=10 and α=0.25 is considered. It is seen from the results that performance degrades with increase in number of sub-carriers. The FF-PTS also shows performance trend similar to IPTS and OPTS. On increasing the sub-carrier from 32 to 512, performance penalty close to 2 dB is observed.

3.4.3 Computational complexity analysis of FF-PTS technique

Firefly algorithms has two inner loops in training process which include the population G_n, and one outer loop for iteration K. So, the computational complexity of the algorithm is calculated by $O({G_n}^2K)$ [98]. The computational complexity here is represented by the number of addition and multiplication performed by the optimization algorithm. So, in FF-PTS technique, the searching complexity is given by the square of the number of fireflies G_n multiplied by the number of iterations K. Similarly, for conventional OPTS technique, computational complexity is calculated as W^{M-1}, where W is the number of phase rotation vectors, and M is represented by total number of sub-blocks.

Table 3.3 presents the CCDF vs PAPR Performance and Computational Complexity analysis of PTS and FF-PTS techniques at CCDF of 10^{-2} for different number of sub-carriers N, sub-blocks M and iterations K. The results shows that the PAPR performance improves with an increase in the number of α for FF-PTS technique but causes premature convergence. For α = 1.0, the improvement in the PAPR performance is seen but it was limited up to CCDF = 10^{-2} and needs more number of OFDM samples to find optimum search space. Similarly for α

= 0.25 the Table 3.4 presents the results at CCDF = 10^{-3}. When the number of sub-blocks M = 8 and number of iterations K = 10 with phase vector W =2, the search complexity for FF-PTS is 1,000, which is greater than the computational complexity of OPTS, which is 128. But, on the other hand, when the number of sub-blocks M is increased up to 16, then the computational complexity of FF-PTS remains unchanged at 1,000, which is lower than the computational complexity of PTS which is calculated to be 32768. FF-PTS suffers from higher computational complexity for a small number of sub-blocks, but as the number of sub-blocks increases, complexity remains constant but PAPR improves as compared to conventional PTS schemes. From this table, i.e. comparative analysis between conventional PTS and FF-PTS method it can be observed that FF-PTS technique reduces the PAPR of original OFDM signal efficiently.

Table 3.3: Comparison of computational complexity of different methods at CCDF = 10^{-2}, Modulation format : 16-QAM

Methods	**Combinations**	**Computational Complexity**	**PAPR (db)**
OPTS	M=8, N=256, W=2	(W^{M-1})= 128	6.4
	M=16, N=256, W=2	(W^{M-1})= 32768	6.0
IPTS	M=8, N=256, W=2	$(W \times M)$= 16	8.4
	M=16, N=256, W=2	$(W \times M)$= 32	7.4
FF-PTS	M=8, N=256, W=2, G_n=10, K=10, $\alpha = 1.0$	$({G_n}^2K)$= 1000	6.6
	M=16, N=256, W=2, G_n=10, K=10, $\alpha = 1.0$	$({G_n}^2K)$ = 1000	6.2

It is observed from the simulation results that the FF-PTS technique provides higher accuracy when the population size is high. Although, the FF-PTS technique has the advantage of being precise, robust, easy and parallel in implementation, it has the disadvantage of possibility of local optima and no memory limitations.

Table 3.4: Comparison of computational complexity of different methods at CCDF $= 10^{-3}$, Modulation format : 16-QAM

Methods	**Combinations**	**Computational Complexity**	**PAPR (db)**
OPTS	M=8, N=256, W=2	(W^{M-1})= 128	6.5
	M=16, N=256, W=2	(W^{M-1})= 32768	6.1
IPTS	M=8, N=256, W=2	$(W \times M)$= 16	8.6
	M=16, N=256, W=2	$(W \times M)$= 32	7.6
FF-PTS	M=8, N=256, W=2, G_n=10, K=10, $\alpha = 0.25$	$(G_n{}^2K)$= 1000	7.8
	M=16, N=256, W=2, G_n=10, K=10, α =0.25	$(G_n{}^2K)$= 1000	7.2

3.5 Summary

FF-PTS algorithm to search for an optimum phase factor combination of OFDM signals has been presented in this chapter. The results shows similar trends in performance as seen in IPTS and OPTS for variation in number of sub-blocks, sub-carriers and modulation format. The performance of the algorithm can be summarized as:

- FF-PTS algorithm requires tuning of large amount of parameters termed as α, β_0, γ, K and G_n.
- Large value of α prevents the algorithm from converging too early, but at the cost of requiring more iterations to settle on a solution and limiting the system performance.
- The algorithm can be trained with very small number of iterations i.e. K=10.
- PAPR performance improves with increase in population size G_n leading to higher complexity.
- Increasing the number of sub-blocks provides consistent performance gain, which is similar to other algorithms.

- The performance shows uniform degradation with increase in number of sub-carriers. This is in agreement with the other techniques (IPTS and OPTS).

- For large number of sub-blocks i.e. M=16, more OFDM samples are required for convergence.

- The performance of FF-PTS is always in between IPTS and OPTS for all similar conditions across variation in all parameters.

CHAPTER 4

Cuckoo Search based PTS (CS-PTS) for PAPR Reduction in OFDM

"Nothing in life is to be feared, it is only to be understood. Now is the time to understand more, so that we may fear less."

Marie Curie

Contents

4.1 Introduction

Cuckoo search (CS) algorithm is another heuristic algorithm that has been significantly appears in many optimization problems. As the change in heuristic algorithm affects the final optimal value of the objective funtion, so it becomes imperative to attempt the use of CS algorithm for our problem. In this chapter, we propose a bio-inspired meta-heuristic phase optimization scheme based on Cuckoo Search (CS-PTS) algorithm, which has the capability to significantly reduce the PAPR of OFDM signals. An important advantage of this algorithm is its simplicity. Compared to other population or agent-based meta-heuristic algorithms like particle swarm optimization and harmony search, CS algorithm has very few parameters to be adjusted. Therefore, it is easy to implement. In PAPR minimization, this scheme searches for a better combination of phase vectors and provides a solution that offers good performance in terms of solution quality and convergence speed. Simulation results shows that the CS-PTS phase optimization technique can achieve improved PAPR reduction in performance as compared to conventional PTS schemes with low computational complexity even for larger number of sub-blocks compared to other PTS techniques.

4.2 Cuckoo Search Algorithm

Cuckoo are fascinating birds, not only because of the beautiful sounds they make, but also because of their aggressive reproduction strategy. Cuckoo Search (CS) is a new meta heuristic search algorithm based on cuckoo birds behavior, which was proposed by Yang and Deb in 2009 [67]. Cuckoo search is a population heuristic algorithm for global optimization and it is one of the evolutionary techniques, inspired by the reproduction strategy of cuckoos. At the basic level as per the behavior of cuckoo bird, if a host bird discovers that the eggs are not their own, it will either throw the alien eggs away or simply abandon its nest and build a new nest elsewhere. Recent studies indicate that CS is potentially far more efficient than PSO and genetic algorithms [87, 99].

For an optimization problem, the quality or fitness of a solution can simply be proportional to the value of the objective function. Other forms of fitness can be defined in a similar way as to the fitness function in genetic algorithms. For simplicity, we can use the following simple representations that each egg in a nest represents a solution, and a new cuckoo egg represent a new solution, the aim is to use the new and potentially better solutions (cuckoos) to replace a not so good solution in the nests. This algorithm can be extended to the more complicated case where each nest has multiple eggs representing a set of solutions. In our work described in this chapter, the simplest approach has been used, where each nest has only single egg and there is no distinction between an egg, a nest or a cuckoo, as each nest corresponds to one egg which also represents one cuckoo.

Furthermore, cuckoo search has two search capabilities: local search and global search, controlled by a switching/discovery probability. The local search is very intensive with about 1/4 of the search time (for $\rho_d = 0.25$), while global search takes about 3/4 of the total search time. This allows that the search space can be explored more efficiently on the global scale, and consequently the global optimality can be found with a higher probability [100].

Another advantage of cuckoo search is that, its global search uses Lévy flights or process [67], rather than standard random walks. Lévy process do not, in general, have an infinite mean and variance. The CS can explore the search space more efficiently than algorithms using standard Gaussian processes. This advantage, combined with both local and search capabilities and guaranteed global convergence, makes cuckoo search very efficient. Various studies and applications have demonstrated that cuckoo search is an efficient technique for optimization problems [98, 101, 102].

4.2.1 Structure of Cuckoo Search Algorithm

The Cuckoo Search optimization algorithm used here has three idealized rules:

- Each cuckoo lays one egg at a time in a random nest, which represents a set of solution co-ordinates.
- A fraction of the nests containing the best eggs, or solutions are carried over to the next generation.
- The number of nests is generally fixed and there is a probability that a host can discover an alien egg. If this happens, the host can either discard the egg or the nest and these results in building a new nest in a new location.

4.2.2 Characteristics of Cuckoo Search Algorithm

In cuckoo search, each egg can be regarded as a solution. In the initial process, each solution is generated randomly. When generating i^{th} solution in $t+1$ generation, denoted by z_i^{t+1}, a Lévy flight is performed as follows:

$$z_i^{t+1} = z_i^t + \alpha \oplus \textit{Lévy}(s, \lambda), \tag{4.1}$$

where

$$\textit{Lévy}\,(s, \lambda) = \frac{\lambda\Gamma(\lambda)\sin\left(\pi\lambda/2\right)}{\pi}\frac{1}{s^{1+\lambda}}, s >> s_0 > 0 \tag{4.2}$$

Here $\alpha > 0$ is the step size s which should be related to the scales of the problem of interests. In most cases, the value of α can be equal to 1. The product $\oplus$ means entry-wise multiplications. This entry-wise product is similar to those used in PSO [99], but here the random walk via Lévy flight is more efficient in exploring the search space as its step length is much longer in the long run [67].

The above equation is essentially the stochastic equation for a random walk. In general, a random walk is a Markov chain whose next state/location only depends on the current location (the first term in the above equation (4.4)) and the transition probability (the second term). However, a substantial fraction of the new solutions should be generated by far field randomization and their locations should be far enough from the current best solution; this will make sure that the system will not be trapped in a local optimum.

As there are two branches in the updating formulas, the local search step only contributes mainly to local refinements, while the main mobility or exploration is carried out by the global search step. In order to simplify the analysis and also to emphasize the global search capability, we now use a simplified version of cuckoo search. That is, we use only the global branch with a random number $r \in [0, 1]$, compared with a discovery/switching probability ρ_d. Now we have

$$\begin{cases} z_i^{t+1} \leftarrow z_i^t & \text{if } r < \rho_{\mathrm{d}} \\ z_i^{t+1} \leftarrow z_i^t + \alpha \oplus L(s, \lambda) & \text{if } r > \rho_{\mathrm{d}} \end{cases} \tag{4.3}$$

The CS algorithm is a stochastic search algorithm and can be summarize with following key steps [103]:

1. Randomly generate an initial population of G_n nests at the positions, $Z = \{z_1^0, z_2^0 \cdots z_n^0\}$, then evaluate their objective values so as to find the current global best g_t^0.

2. Update the new solutions/positions by

$$z_i^{t+1} = z_i^t + \alpha \oplus L\acute{e}vy(\lambda), \tag{4.4}$$

3. Draw a random number r from a uniform distribution [0, 1]. Update z_i^{t+1} if $r > \rho_d$. Then, evaluate the new solutions so as to find the new global best g_t^*.

Table 4.1: Cuckoo Search Analogy with PTS Analogy

Cuckoo Search Analogy	**PTS Analogy**
Aim= Optimal reproduction of nest	Aim= Optimize the objective function
Cuckoo Eggs	Phase Vector
Population	No of Solution
Generation	Iteration
Random nests	Random solution
while ($F_i < F_j$)	Current Sol < Previous Sol
If true, previous nest is selected and updated	Previous is the solution
If false, current nest is updated	Current is the solution
Worst nest found with p_d probability	Replace the solution with the other random solution
Repeat this up to $t < MaxIterK$	Repeat this up to best solution
Best objective nest after all iterations	Best solution after all iterations

4. If the stopping criterion is met, then g_t^* is the best global solution found so far. Otherwise, return to step (2).

In the real world, a cuckoo's egg is more difficult to be found when it is more alike to the host's eggs. So the fitness is related to the difference and that is the main reason to use a random walk in a biased way with some random step sizes.

The analogy of PAPR parameters with CS parameters is explained using Table 4.1. The parameters considered are in terms of PTS optimization.

4.3 PAPR minimization using Cuckoo Search Algorithm

In order to process the OFDM signals for minimum PAPR, a suboptimal combinatorial method based on Cuckoo Search algorithm (CS) is used here to solve the optimization problem of PTS. CS-PTS algorithm has capability to provide better PAPR performance as compared to conventional PTS algorithm.

The minimum PAPR for PTS method is relative to the problem and the aim is to

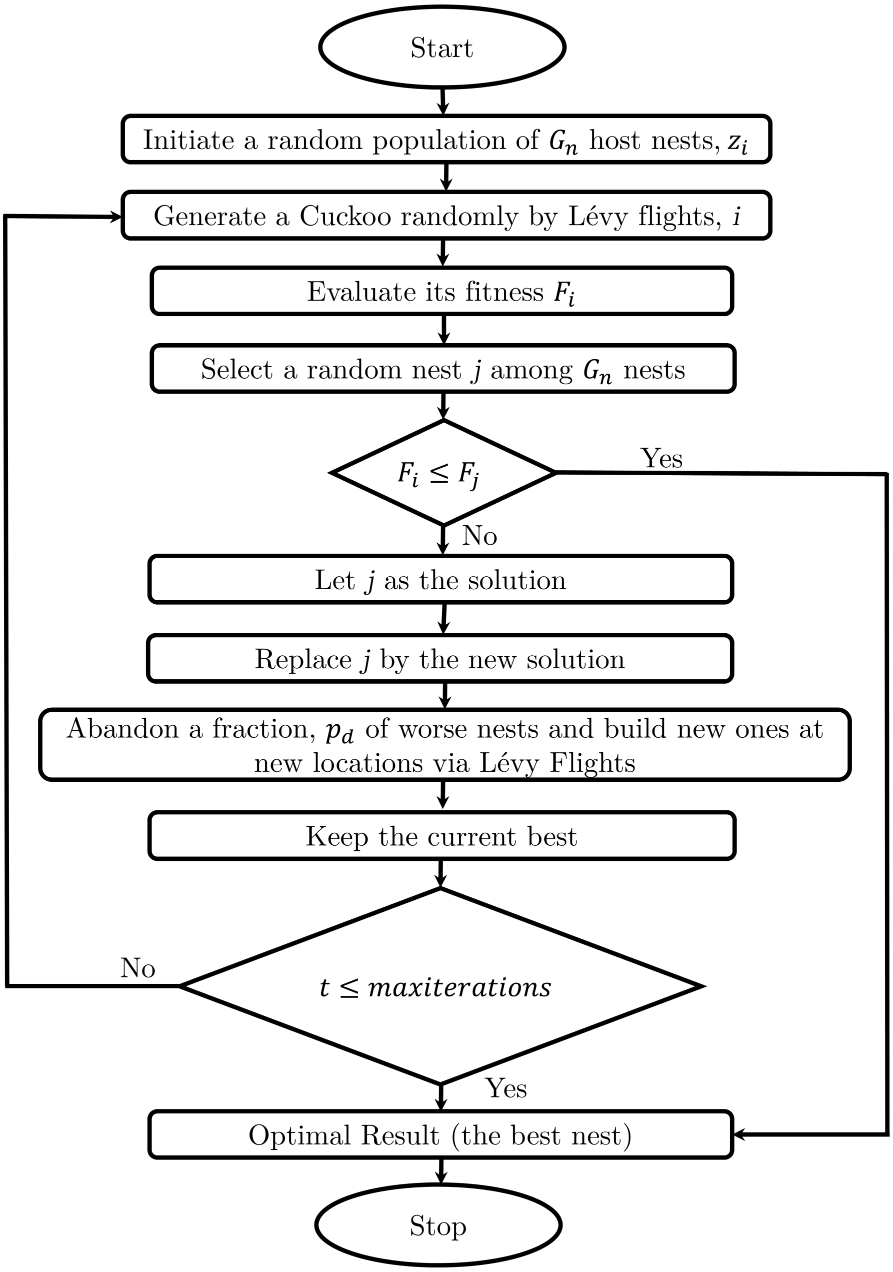


Figure 4.1: Flow chart of Cuckoo Search algorithm

:

Minimize

$$f(b) = \frac{\max\left[|x(b)|^2\right]}{E\left[|x(b)|^2\right]} \tag{4.5}$$

subject to

$$b \in \left\{ e^{j\phi_m} \right\}^M \tag{4.6}$$

where $\phi_m \in \left\{ \frac{2\pi k}{W} \,|k = 0, 1, ..., W-1 \right\}$.

The original Cuckoo Search algorithm is only suitable for continuous numerical optimization problems, some modifications need to be applied on the original Cuckoo Search algorithm to search for better combinations of phase factors for PTS. We refer to the Cuckoo Search algorithm as CS-PTS.

From an implementation point of view, it has been considered that each egg in a nest represents a solution i.e. various combinations of phase vectors, and a cuckoo egg represents a new solution. The objective is to use the new and potentially better solutions i.e. cuckoos to replace average solution in the nests. In the simplest form, each nest has one egg. Here CS-PTS algorithm is applied to search the optimum combination of phase factor for PTS.

Based on the above analysis, the basic steps of CS-PTS technique can be summarized as the pseudo code shown in Algorithm 2.

The steps involved in CS-PTS algorithm are as follows:

- **Parameter initialization :**

  In the CS-PTS algorithm, a cuckoo's egg represents a phase vector $b_i = [b_{i,1}, b_{i,2}, ...b_{i,M}]$, where $i = 1, 2...G_n$, where G_n denotes the size of a randomly distributed initial population. The specified parameters to be initialized include: Number of nests (or different solutions) G_n=16; Discovery rate of alien eggs/solutions p_d=0.25; Upper and lower search space limits is taken as Upper bound (b_i^{max}) = 1, Lower bound (b_i^{min}) = -1 and stopping criterion K.

- **Host nests population initialization :**

  Initially the set of possible phase factor combinations is identified as the

Algorithm 2 Cuckoo Search Algorithm for PTS based PAPR reduction (CS-PTS)

Objective function $f(b), b \in \left\{e^{j\phi_m}\right\}^M$
Generate an initial population of host nests $b_i = [b_{i,1}, b_{i,2}, ...b_{i,M}]$, where $i = 1, 2...G_n$
while ($t <$ Max Iteration K) or (stop criterion)
    Find new nests using Lévy flight as:
    for i=1 to G_n (all nests)
        for t= 1 to K
            Set $newnest[b_i(t+1)] \leftarrow currentnest[b_i(t)]$ +stepsize(α) $\times$ Lévy sample(λ)
        end for
    end for
    Evaluate the new nests against the objective function and calculate their quality/fitness:
    Rank and keep the current best nest as:
    for i=1 to G_n
        if $newnest[b_i]$ is better than $currentnest[b_i]$
            replace $currentnest[b_i]$ by the new solution $newnest[b_i]$;
        end if
    end for
    Replace a fraction (p_d)of nests as:
    Get two permutation random arrays $[b_i^{min}]$ and $[b_i^{max}]$ of G_n length;
    for i=1 to G_n
        for t= 1 to K
            if $randomsample() \leq \rho_d$
                Set $newnest[b_i] \leftarrow randomsample() \times$ (nest$[b_i^{max}] - nest[b_i^{min}]$)
            end if
        end for
    end for
    Evaluate the best solutions (or nests with quality solutions) at new locations via Lévy flights;
    Rank the solutions and find the fitness of current best new nests;
end while
Post-processing the results and visualization;

available nests. Each row in the matrix is a set of solution computed by evaluating the objective function between lower and upper bound values which results in randomly populating set of solutions computed by each structure ($i = 1, 2, ...n$), the objective function $f(x)$ is evaluated, which takes the value from the collection $\{+1, -1\}$.

- **New solution (eggs) construction :**

  Generation of new solutions $b_i(t+1)$ for a cuckoo i in CS algorithm is based on the Lévy flight and calculated by following formula,

$$b_i(t+1) = b_i(t) + \alpha \cdot \text{Lévy}(\lambda), \tag{4.7}$$

  where $\alpha > 0$ is the step size which should be related to the scales of the problem. Lévy flight is used to generate the new phase factor value using Mantegna's algorithm with step size A. Lévy flight elects a new phase value with the value from the combinations of phase vectors b_i. The b_i' values are as follows:

$$b_i' = \exp\left(\frac{j2\pi k}{W}\right); \quad k \in \{0, 1, \ldots W-1\} \tag{4.8}$$

  The process is repeated in each iteration until the bottom values are replaced by new phase factor values.

- **New nests update :**

  The generation of top phase factor values is slightly different from the bottom nests. The first phase factor value with its PAPR value is compared with the PAPR value of the randomly chosen phase factor value from the available phase factor combination. If the new PAPR value is less than the existing PAPR, then existing value is replaced by the new value. In case both the new and existing values are same, the Lévy flight step is applied to choose randomly the new phase factor value and then it is updated by following formula:

$$b_i = b_i^{min} + (b_i^{max} - b_i^{min}) \times rand \in (0, 1) \tag{4.9}$$

  where b_i^{max} and b_i^{min} are the upper and lower search space limits respectively.

Once all the phase factors contributing to generating the new phase factor combination via CS Lévy flight are used, the phase factor with the best PAPR values are used in the next generation. this is equivalent to replacing the old eggs with new one.

- **Stopping criterion :**
  Above Algorithm is repeated till the total number of function iterations K is reached i.e. top phase factor values are compared with the new phase factor values. The optimum phase factor combination producing least PAPR value is obtained once the $(G_n - 1)$ generations were completed. Thus, CS-PTS algorithm efficiently reduces the computation complexity to optimize the best PAPR with less computational complexity.

4.4 Simulation Results and Discussions

To evaluate the performance of CS-PTS algorithm in PAPR reduction of OFDM signals, extensive simulations have been conducted. To generate the CCDF of the PAPR, 10,000 OFDM symbols of 16 QAM modulated signals were randomly generated. Following this, the transmitted signal was oversampled by a factor of 4 for accurate PAPR. The performance of CS-PTS was compared with conventional PTS techniques. The process of signal generation was similar to the process described in section 3.

4.4.1 CS-PTS algorithmic parameter variation for PAPR performance

In CS optimization, there are three control parameters to be adjusted. These include number of nests (G_n), maximum number of iterations (K) and probability of an alien egg to be discovered (ρ_d) also termed as discovery rate. Among these

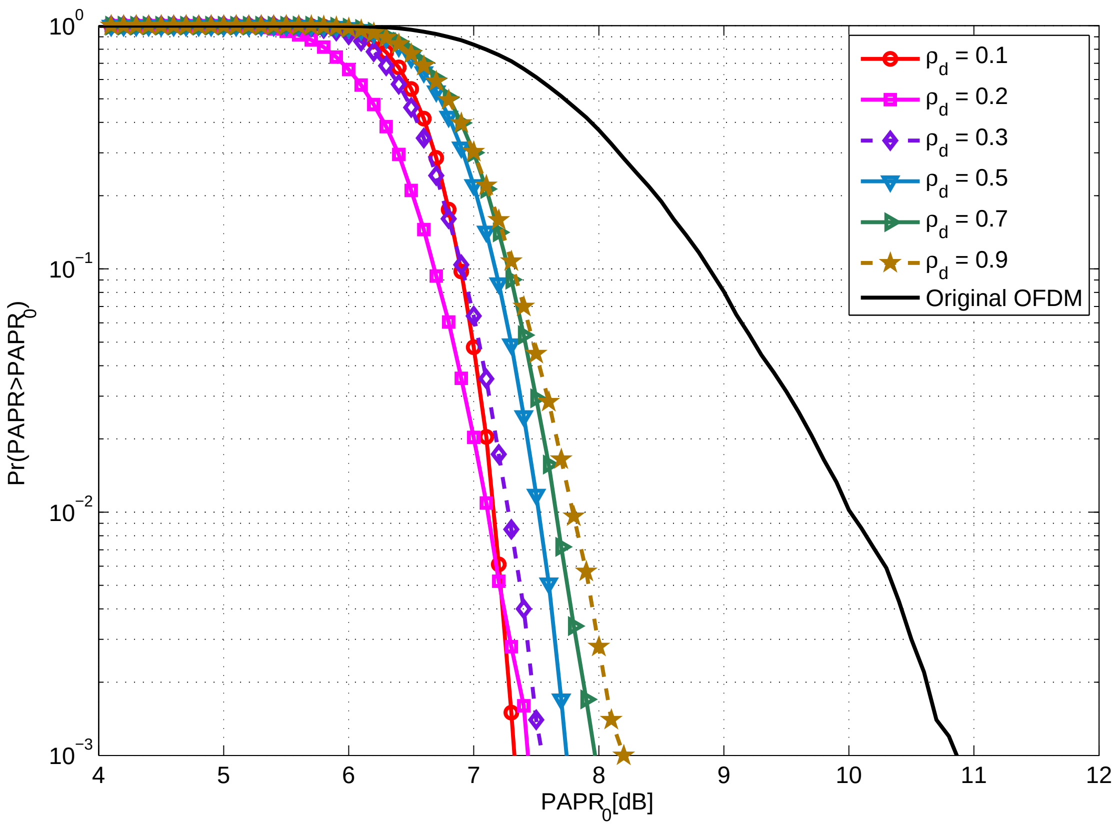


Figure 4.2: CCDF vs PAPR performance of CS-PTS technique for different values of ρ_d, when N= 256, M=16, W=2, G_n=16

parameters, the number of nest (G_n) and maximum number of iterations (K) were fixed in advance depending on the considered systems.

4.4.1.1 Variation in discovery rate ρ_d

For small-scale systems like phase factor optimization with simple constraints, the number of nest and maximum number of iterations can be set to small values in the range 10 to 50. Selection of number of nests (G_n) and maximum number of iterations (K) has been analyzed in subsequent subsections. The most important parameter of the proposed method is the discovery rate, which is the probability ρ_d has a large effect on the final solution. This parameter should be tuned since it is a random number and generally there are no criteria for a proper selection.

Table 4.2: Results by CS-PTS for PAPR values with different values of ρ_d

$\boldsymbol{\rho_d}$	**PAPR at CCDF=10^{-2} (dB)**	**PAPR at CCDF=10^{-3} (dB)**
0.1	7.2	7.2
0.2	7.1	7.3
0.3	7.3	7.4
0.4	7.4	7.5
0.5	7.5	7.7
0.6	7.6	7.8
0.7	7.7	7.9
0.8	7.8	8.0
0.9	7.9	8.2

Therefore, the effect of ρ_d on the final solution by the CS-PTS method for each test system has been analyzed with the value of ρ_d ranging from 0.1 to 0.9 with a step size of 0.1. The result of effect of ρ_d as shown in Figure 4.2.

Table 4.2 presents the CCDF vs PAPR performance of CS-PTS system for ρ_d = 0.1 to 0.9 with CCDF = 10^{-2} and 10^{-3}, where N = 256, M=8, K=10 and W=2 is considered. From the result it is seen that, the PAPR performance for ρ_d =0.1 has a different trend than other values of ρ_d. Initially the PAPR performance for ρ_d =0.1 is inferior to all other values and later it improves with a performance superior than others. Whereas, other values of ρ_d between 0.2 to 0.9 shown uniform characteristic. There is a minor change in PAPR performance when ρ_d changes between 0.2 to 0.3. Higher than 0.3, the PAPR performance degrades more. Considering these trends, ρ_d value was selected to be at midpoint of 0.2 and 0.3 (which is 0.25) for further analysis.

4.4.1.2 Variation of population size G_n

Population size plays an important role in optimization of the algorithm. Figure 4.3 and 4.4 presents some results of the CCDF of the PAPR simulated for different

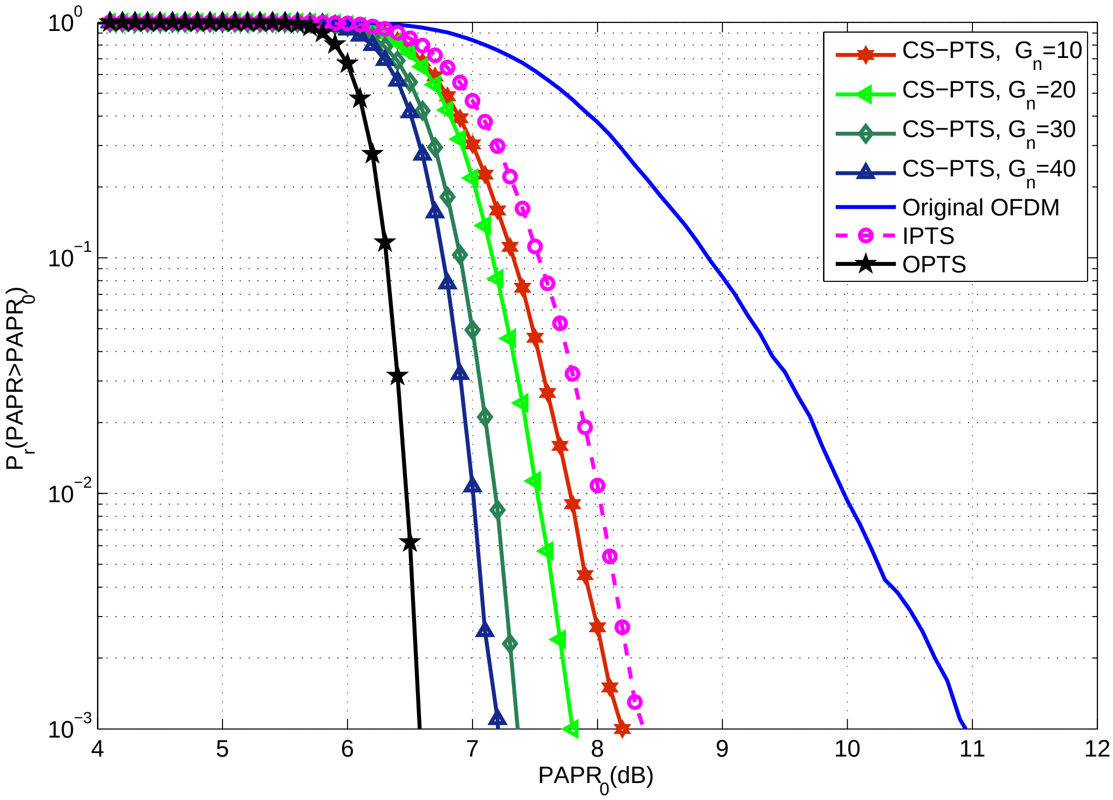


Figure 4.3: CCDF vs PAPR performance of CS-PTS technique for different G_n, when M=8, N= 256, W=2, K=10

number of host nests i.e. generations(G_n) for CS-PTS system with 256 sub-carriers, in which M=8 and 16 sub-block employing random partition and the phase weight factor W =2, uniformly distributed random variables are used for PTS technique. It is clear from the simulation results that the CCDF of the PAPR shows improved performance on increasing the numbers generations due to the limited number of phase weighting factor. As the numbers of generations increases, the CCDF of the PAPR also improves. For generation value G_n = 10, 20, 30 & 40, it is seen that the CS based PTS technique is capable of attaining optimum performance gain of 0.4 dB between G_n = 10 to 20 as compared to IPTS technique with CCDF of 10^{-3}. On increasing the generation/population G_n from 20 to 40, a performance gain of 0.2 dB is observed at CCDF of 10^{-3}. Considering these, G_n =16 was selected

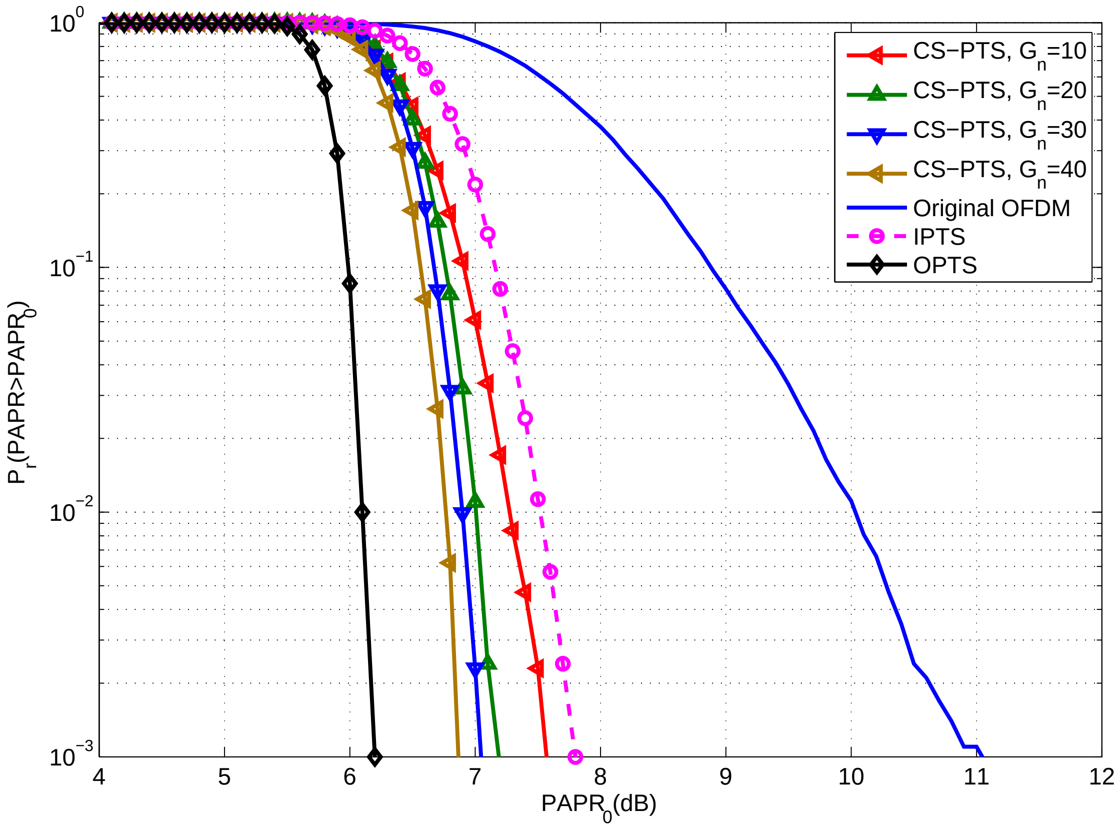


Figure 4.4: CCDF vs PAPR performance of CS-PTS technique for different G_n, when M=16, N= 256, W=2, K=10

for further analysis, since it is close to the mid-point. It may be noted that higher values of G_n increases the complexity of search space leading to increased computational complexity.

Various simulations were also performed to analyze the performance of number of host nests (or the generation G_n) and the probability p_d for CS-PTS optimization technique. We have used G_n = 5, 10, 15, 20, 30, 40, 50, 100, 150, 250, 500 and p_d = 0, 0.01, 0.05, 0.1, 0.15, 0.2, 0.25, 0.3, 0.4, 0.5. It can be seen from the simulation results that G_n = 15 to 40 and p_d = 0.25 provides optimum values for CS-PTS optimization technique. Results and analysis also confirm that the convergence rate is not sensitive to the parameters used up to some extent. This means that the fine adjustment is not essential for CS-PTS optimization technique.

Table 4.3: CS-PTS Simulation Parameters

Simulation Parameters	**Type/Value**
Number of sub-carriers (N)	128, 256, 512
Number of sub-blocks (M)	4, 8, 16
OFDM Blocks	10,000
Oversampling Factor (L)	4
Bits per symbol (b)	4
Phase rotation factors (W)	$\{+1, -1\}$
Population of host nests (G_n)	16
Scaling factor (β)	1.5
Discovery rate of alien eggs/solutions (p_d)	0.25
Constellation Size	16-QAM
No. of iterations (K)	10, 20, 30, 40

For CS-PTS algorithm, simulation parameters are give in Table 4.3. It is further seen that when these optimizations are applied to optimize the phase factor in PTS method, the PAPR is reduced in each case.

4.4.1.3 Variation in number of iterations K

To analyze the effect of number of iterations K on PAPR reduction using CS algorithm, simulation was carried out using parameters presented in Table 4.2. Figure 4.5 compares the CCDF vs PAPR performance of CS-PTS system as function of number of iterations K with N= 256, M= 8 and W=2. When the number of iterations are 5, then PAPR of CS-PTS is 8.15 dB. On increasing the number of iterations, the PAPR for FF- PTS is approximately 8 db for 10, 50, 100 and 500 iterations as presented in Figure 4.8 at CCDF of 10^{-3}. It is observed that the number of iterations K has very little effect on the PAPR performance of CS-PTS. However with increase in iterations, the processing time gets longer due to increased function evaluation leading to increased computation complexity. From results, it is observed that iterations beyond 10 do not yield any additional per-

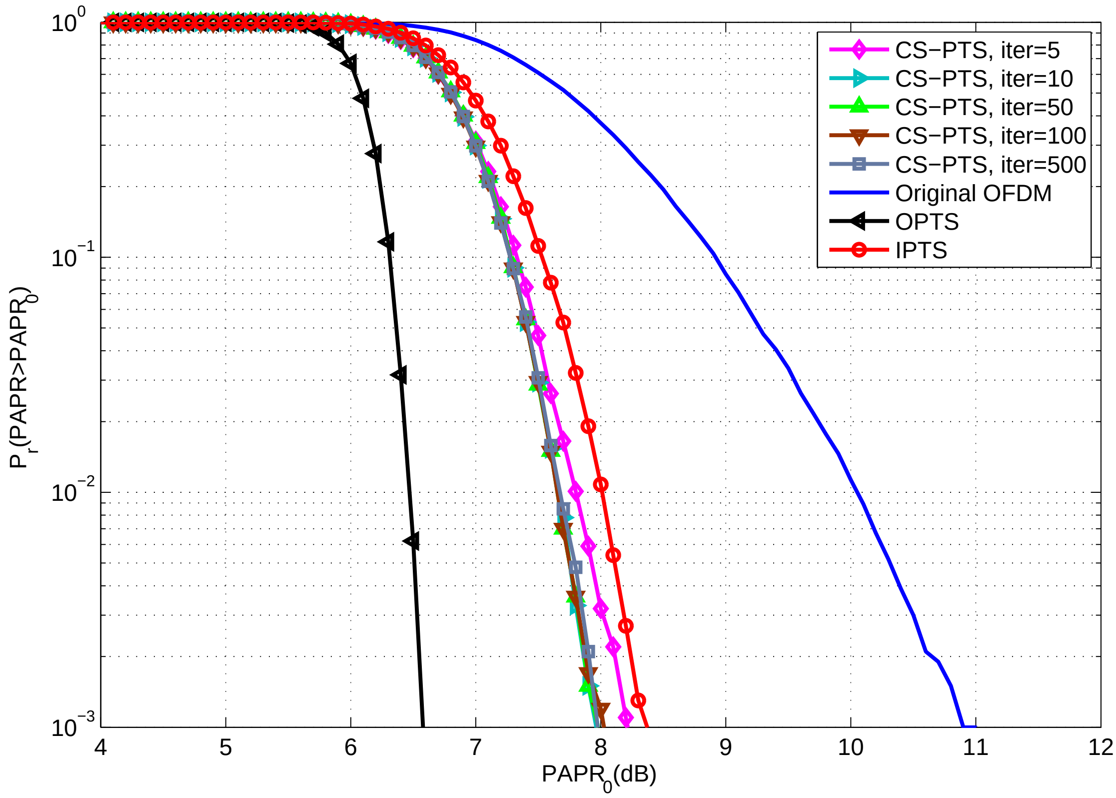


Figure 4.5: CCDF vs PAPR performance of CS-PTS technique for different iterations, when N= 256, M=8, W=2, G_n=16

formance gain. Therefore, an appropriate iteration number K =10 was considered for all further studies to achieve the best trade-off between the PAPR reduction performance and complexity.

Figure 4.6 shows the evolution curve of CS-PTS technique, which represents graph between mean of best cost function values i.e. PAPR and iterations. It is well known that increasing the number of iterations will cause an increase in searching complexity. So, from this description, we can see that the CS-PTS is effective technique for reducing the PAPR and has very little improvement after increasing the number of iterations from 10 to 100. So, we can take optimum value of iteration number K =10 for CS-PTS scheme, which will provide good tradeoff between the PAPR performance and computational complexity [60]. Simultane-

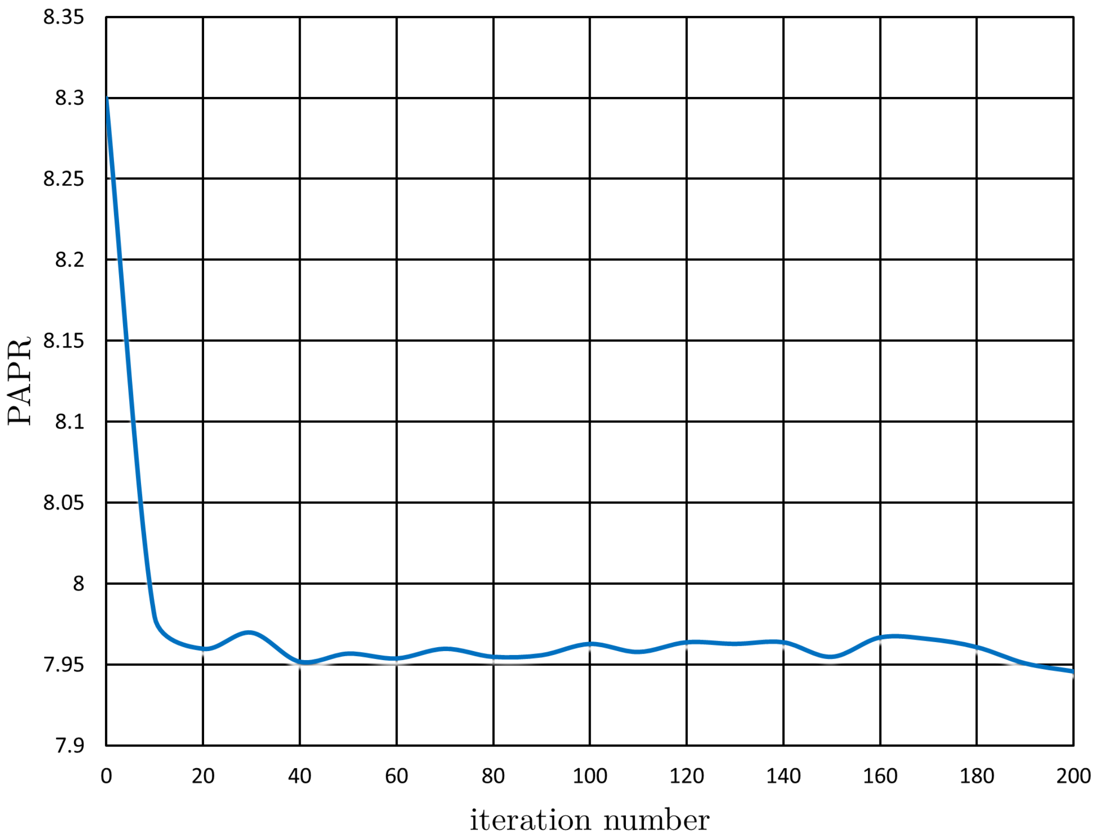


Figure 4.6: Evolution curve of CS-PTS algorithm

ously , it introduces a PAPR threshold for terminating the searching dynamically and avoids unnecessary searches. If the output result is higher than the threshold, the population size can be increased to expand effective searching range and hence improve the performance.

4.4.2 Effect of variation in OFDM system indices on PAPR performance

Sensitivity of the algorithmic parameters were discussed in the previous subsection. Following this, the performance of CS-PTS has been evaluated for different parameters.

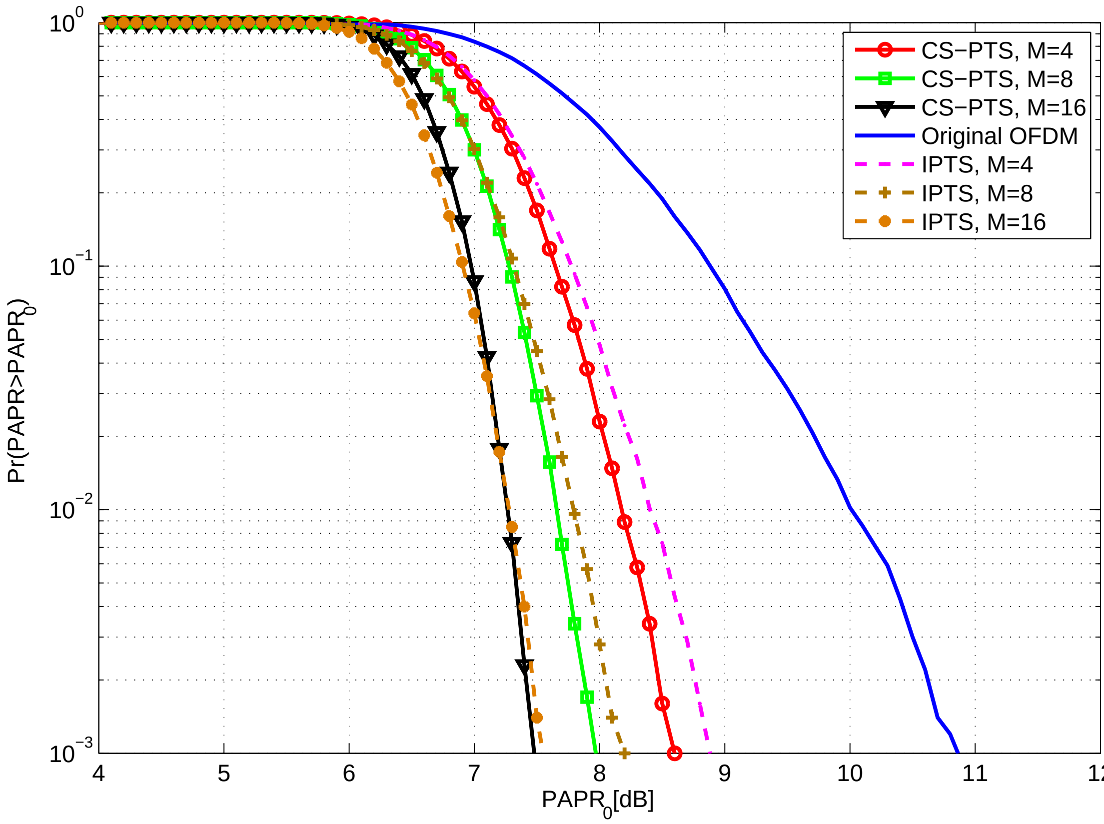


Figure 4.7: CCDF vs PAPR performance of CS-PTS technique for M= 4, 8, 16 sub-blocks, when N= 256, W=2, G_n=16, K=10

4.4.2.1 CCDF vs PAPR performance with variation in number of sub-blocks M

Figure 4.7 illustrates CCDF vs PAPR performance of the CS-PTS system for M=4, 8 and 16 sub-blocks with N= 256 and W=2. The results have been compared with the traditional PTS technique. It can be seen that, the PAPR of the original OFDM signal is around 10.9 dB with CCDF of 10^{-3}. On application of IPTS and CS-PTS technique for M=4 sub-blocks, the PAPR achieved is around 8.9 dB and 8.6 dB respectively. Under same condition for M= 8 and 16 sub-blocks, it is seen that CS-PTS scheme provides performance comparable to the IPTS technique. For M=8, the PAPR is 8.2 dB after applying IPTS and, after performing CS-

PTS, the PAPR of OFDM signal is 7.9 dB. Similarly for M=16, the PAPR of IPTS and CS-PTS is approximately 7.6 dB and 7.5 dB respectively. Another issue of complexity for PTS method is the number of sub-blocks which is addressed in this result. As the partition of sub-blocks increase, the number of IFFTs to be performed also increases. So, this proposed method obtains the better result with fewer sub-blocks. It can be seen from the results that CS-PTS provides performance gain of 0.4 dB as compared to IPTS for M=4 sub-blocks. Following this, for M=16 sub-blocks, CS-PTS gives similar performance gain as IPTS. Since better PAPR is obtained at minimum sub-blocks, not only the requirement of more IFFT operation is reduced but also the number of side information to be transmitted for recovering the original data block is also minimized.

4.4.2.2 CCDF vs PAPR performance with variation in number of sub-carriers N

In order to investigate impact of number of sub-carriers on the efficiency of CS algorithm, sub-carriers were varied in the range from 128 to 512. Figure 4.8 presents the simulation results of CCDF vs PAPR performance of CS-PTS system for N= 128, 256 and 512 sub-carriers, where M=8 and W=2 is considered. The performance has been compared with the original OFDM, IPTS and CS-PTS algorithm for various sub-carriers. It is known that increase in sub-carriers degrades PAPR. As we can see that the CCDF of the PAPR is gradually improves upon increasing the numbers of sub-carriers due to the limited phase weighting factor. In simulation results, when N= 128, M= 8 and W=2, the PAPR of the IPTS scheme is around 7.8 dB. After applying CS-PTS, PAPR is approximately 7.4 dB with CCDF of 10^{-3} and improvement of approximately 0.4 dB has been seen. In continuation with this, when N= 256, M= 8 and W=2, after applying IPTS and CS-PTS, PAPR are 8.3 dB, 7.9 dB respectively with CCDF of 10^{-3}. However with N= 512 sub-carriers, the PAPR of IPTS and CS-PTS are approximately 8.6

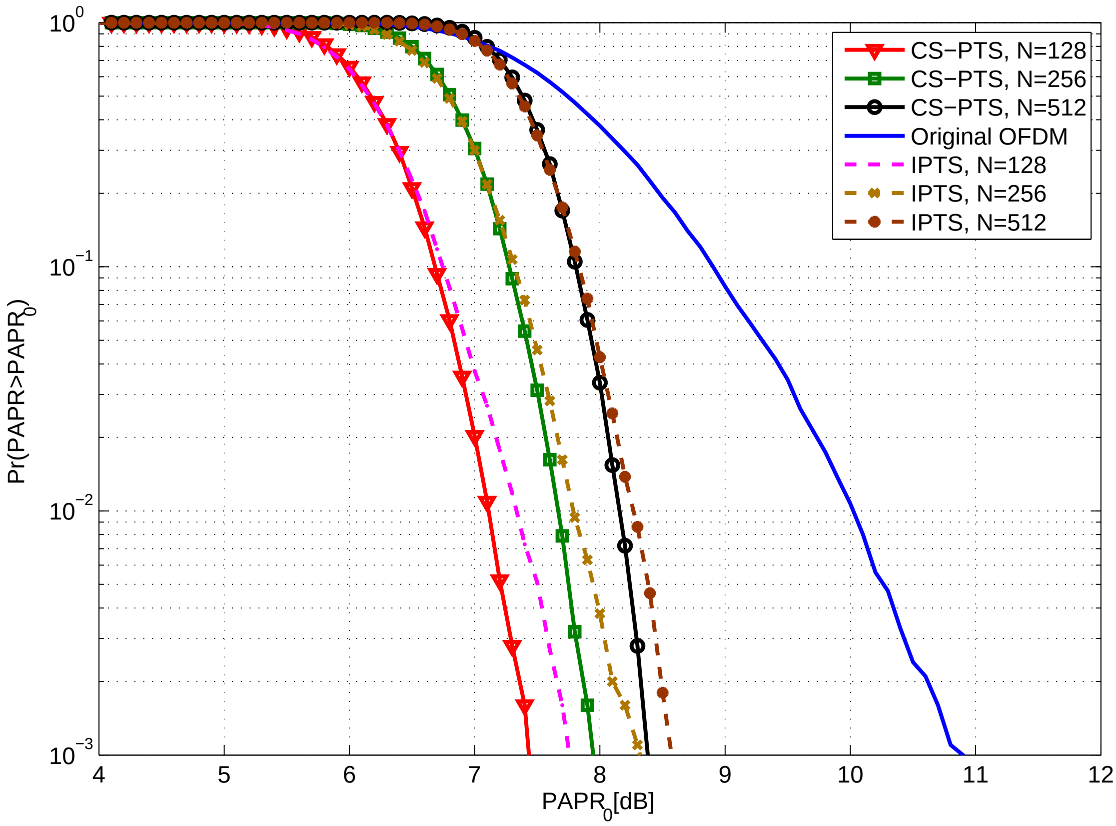


Figure 4.8: CCDF vs PAPR performance of CS-PTS technique for N= 128, 256, 512 sub-carriers, when M=8, W=2, G_n=16, K=10

dB and 8.4 dB respectively. So, it is observed that PAPR values are dependent on number of sub-carriers used and the optimization algorithms based PTS provides improvement in PAPR performance in each case w.r.t. conventional PTS schemes. From above the descriptions, we can see that the CS- PTS an is effective technique for providing more performance difference for small number of sub-carriers and yields lower PAPR performance even with a large number of sub-carriers in an OFDM system.

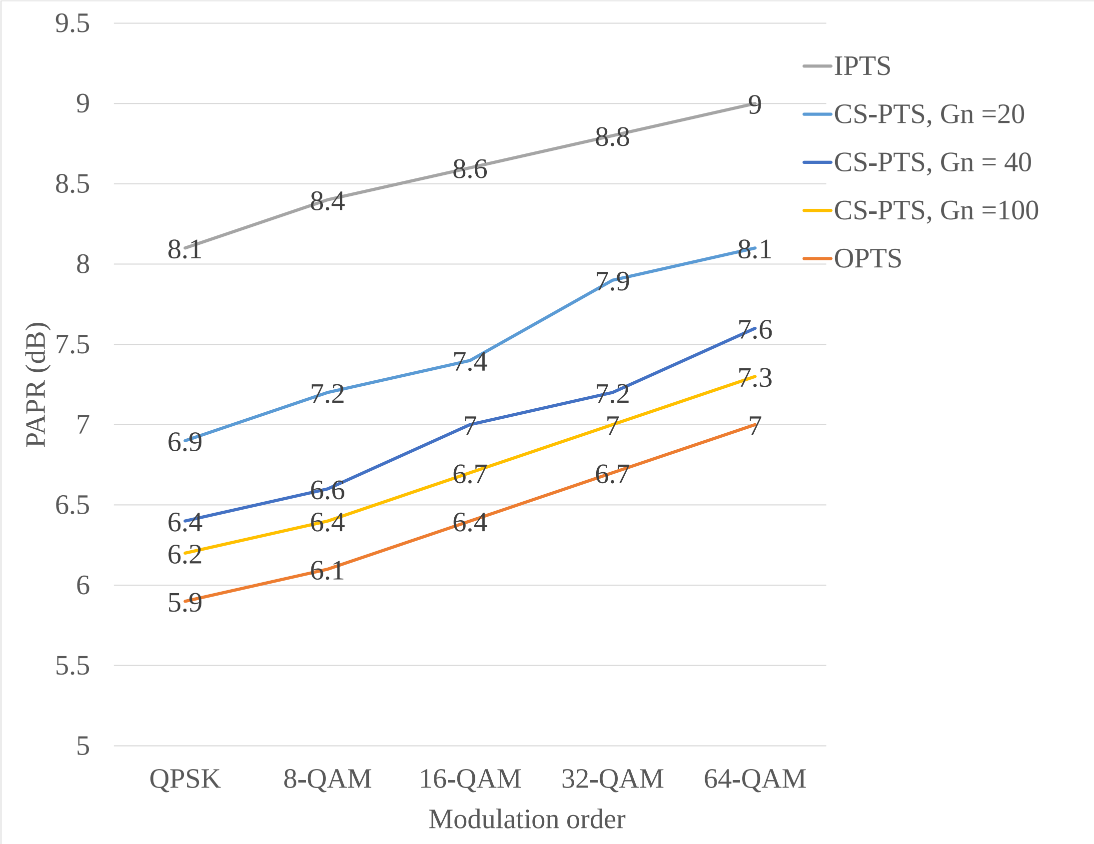


Figure 4.9: CS-PTS performance for different modulation formats

4.4.2.3 CS-PTS performance for different modulation formats

Figure 4.9 presents the PAPR performance of the CS-PTS scheme for different modulation orders like QPSK, 8-QAM, 16-QAM, 32-QAM and 64-QAM. Simulation parameters were taken as M=8 sub-blocks, N=256 sub-carriers, W=2, K=10 iterations and discovery rate ρ_d=0.25. The population size/ generations were considered from 20 to 100. It can be seen from results that CS-PTS provides linear performance for different modulation formats. At G_n=100, PAPR performance of the CS-PTS scheme is superior as compared to OPTS, but at the cost of very high complexity. So, a trade-off between PAPR performance and complexity calculation in terms of population size is required for simulation.

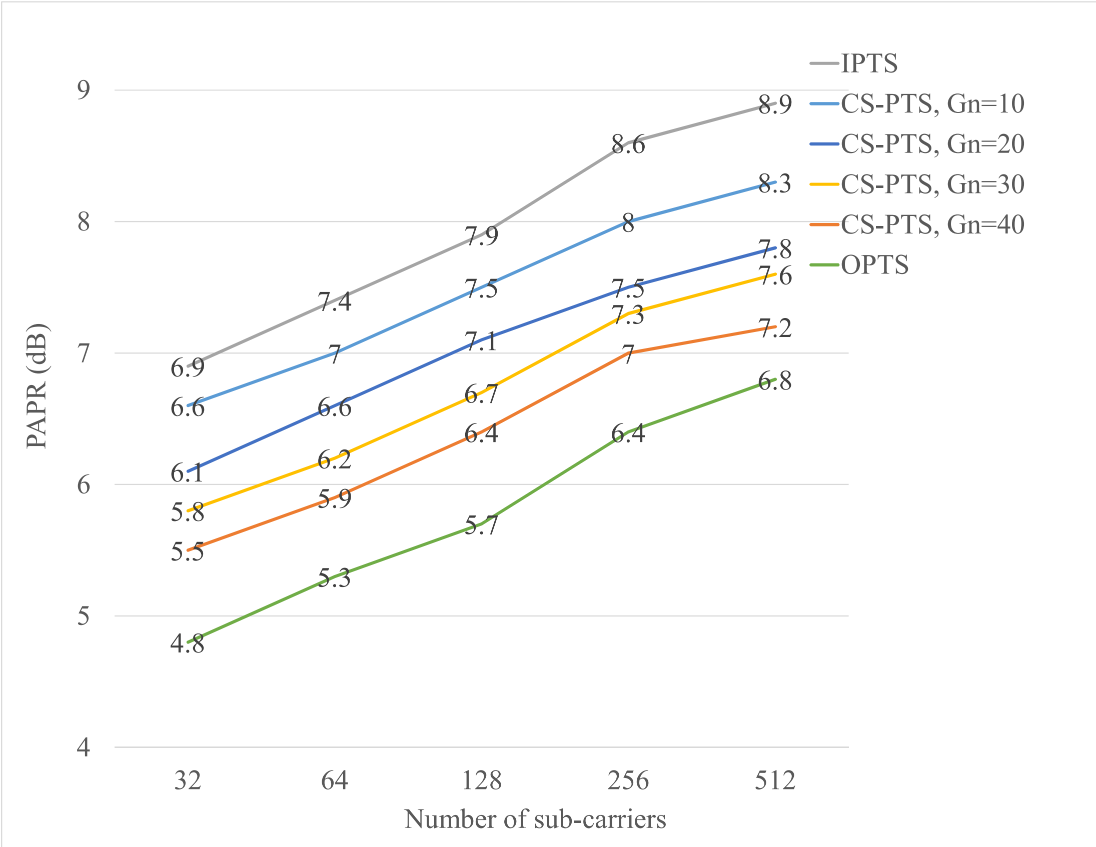


Figure 4.10: CS-PTS performance for different number of sub-carriers

4.4.2.4 CS-PTS performance for different number of sub-carriers

The summarized results presented in Figure 4.10 shows the 16-QAM CS-PTS performance for different number of sub-carriers varied from 32 to 512, when M=8, W=2, K=10 and ρ_d=0.25. It is clear from the results that PAPR performance of the PTS technique will be increased after increasing the number of sub-carriers. As discussed in the previous sub-section, proper selection of the population size G_n is expected based on system requirements and available resources.

4.4.3 Analysis of Computational Complexity

Table 4.4 shows the CCDF vs PAPR Performance and Computational Complexity analysis of 16-QAM OFDM-PTS Technique with IPTS and CS-PTS for different number of sub-carriers N, sub-blocks M, iterations K and generations(G_n).

Table 4.4: Comparison of computational complexity of different methods at CCDF $= 10^{-3}$, Modulation format : 16-QAM

Methods	**Combinations**	**Computational Complexity**	**PAPR (db)**
OPTS	M=8, N=256, W=2	(W^{M-1})= 128	6.5
	M=16, N=256, W=2	(W^{M-1})= 32768	6.1
IPTS	M=8, N=256, W=2	$(W \times M)$= 16	8.2
	M=16, N=256, W=2	$(W \times M)$= 32	7.4
CS-PTS	M=8, N=256, W=2, G_n=16, K=10	$(G_n * (G_n + 1))/2$= 136	7.9
	M=8, N=256, W=2, G_n=40, K=10	$(G_n * (G_n + 1))/2$= 820	7.1
	M=16, N=256, W=2, G_n=16, K=10	$(G_n * (G_n + 1))/2$=136	7.4
	M=16, N=256, W=2, G_n=40, K=10	$(G_n * (G_n + 1))/2$= 820	6.8

For CS-PTS , the searching complexity is given by $(G_n * (G_n + 1))/2$. When the number of sub-blocks M are 8 and number of generations(G_n) are 16 with phase vector W =2, then searching complexity for CS-PTS is 136, which is greater than the computational complexity of OPTS i.e. 128. But, in other case, when number of sub-blocks M has been increased up to 16, then the computational complexity of CS-PTS is 136, which is lower than the computational complexity of OPTS i.e. 32768. In CS-PTS, more computational complexity is required for a small number of sub-blocks, but after increasing the number of sub-blocks, complexity as well as PAPR is less as compared to OPTS. When M = 16, N =256, W = 2, then if G_n = 16 the performance of CS-PTS is not better than IPTS, and incurs a higher computational complexity (of around a factor of 4). It is only when G_n is increased that the performance is better (by 0.6 dB), but with a higher computational complexity (over 20 times higher than for IPTS). When $M = 8$, then CS-PTS outperforms IPTS at $G_n = 40$, however the performance improvement can be as little as 0.3dB for a computational complexity that is over 8 times higher. From this table i.e. comparative analysis between PTS and CS-PTS method, it has been observed that CS-PTS technique reduces the PAPR of original OFDM signal efficiently under certain conditions and performance has been improved with some limitations.

4.5 Summary

In this chapter, Cuckoo Search algorithm PTS algorithm (CS-PTS) has been proposed to search optimum combination of phase factor for OFDM signals. From the comparison study of the performance of CS-PTS algorithm, it also shows that CS-PTS algorithm in combination with Lévy flights is very efficient and proves to be superior as compared to IPTS. The features of CS-PTS can be summarized as under:

- CS-PTS is a simple structure algorithm requiring tuning of only 2 parameters ρ_d and G_n.
- Only K=10 iterations are sufficient for training the network.
- CS-PTS performs better than IPTS for lower number of sub-blocks.
- The system requires close to G_n=20 generations to provide good performance. Beyond this, the performance gain is marginal.
- Variation in modulation order from QPSK to 64-QAM show a performance degradation of close to 1 dB for all techniques (CS-PTS, IPTS and OPTS).

- Variation in sub-carrier also show similar performance degradation 32 to 512 sub-carriers.
- CS-PTS with 16 sub-block shows superior PAPR performance than OPTS only when the number of population size G_n are high. When population size is small, the performance of OPTS with 8 sub-blocks outperforms CS-PTS with 16 sub-blocks. This can be considered as limitation of the algorithm.
- PAPR performance improves after increasing population size G_n but complexity will be increases gradually.

CHAPTER 5

Improved Harmony Search based PTS for PAPR Reduction

"To invent something is to find it in what previously exists".

-Brian Arthur

Contents

5.1 Introduction

Chapter 3 and Chapter 4 presented two bio-inspired techniques Firefly algorithm (FF) and Cuckoo search algorithm (CS) respectively. In this chapter a variant of HS algorithm termed as improved harmony search based PTS algorithm (IHS-PTS) is applied to search for optimum combination of phase vectors for OFDM signal. Compared to the PAPR reduction optimization techniques like conventional PTS scheme, the IHS-PTS algorithm possesses the capability to provide improved PAPR. Due to its simple structure, very few parameters need to be adjusted for larger PTS sub-blocks. IHS algorithm is a derivative of HS algorithm [104]. Simulation results of the IHS-PTS algorithm indicate that it is an efficient and feasible optimization candidate for better PAPR performance.

To reduce the search complexity for optimum phase vectors in PTS, IHS based PTS has been presented to search for phase vectors. For this, the problem can be formulated as an optimization problem which will need a sub-optimal solution to the problem capable of achieving a better trade-off between PAPR performance and computational complexity. Due to the fact that the search for a better combination of phase factors in PTS can be formulated as a combinatorial optimization problem with some constraints, a suboptimal combinatorial scheme derived from a variant of the Harmony Search (HS) optimization algorithm termed the Improved Harmony Search based PTS (IHS-PTS), is proposed to achieve good PAPR reduction with low number of trials. This chapter provides performance analysis for PAPR reduction in OFDM using this improved harmony search algorithm which is derived from HS-PTS [105].

5.2 Harmony Search Algorithm

The Harmony Search (HS) algorithm developed by Geem et al. [106,107] belongs to the group of stochastic search techniques. It is comparatively simpler method that imposes fewer mathematical requirements. Similar to the other stochastic search methods, it randomly selects candidate solutions to the optimization problem from a set of discrete or continuous set of solutions. This selection is verified for its feasibility. If it is found to be feasible, then it is inserted in to harmony search memory, where each candidate solution is stored in a descending order. The method after filling the harmony search memory matrix continuous selection of the new solutions depending on two parameters, either from the harmony memory considering rate (HMCR) or the pitch adjustment rate (PAR). Harmony Search algorithm is comparatively simpler approach as compared to mathematical programming techniques and it neither requires initial starting values for the decision variables nor the derivative information of the objective function and constraints. This makes the HS algorithm easy to implement in combinatorial optimization algorithms.

The basic idea behind the HS algorithm is similar to the ideas of all meta-heuristic algorithms that are found in the paradigms of natural phenomena. Following the idea of meta-heuristic algorithms that they all seek a stable state, the harmony search method derives its roots in the harmony of a musical performance which exists in the nature. Music harmony is a combination of sounds considered pleasing from an aesthetic point of view. Music harmony in nature is a kind of beat phenomenon made by several sound waves, that have different frequencies.

Harmony Search algorithm is based on natural musical performance processes that occur, when a musician searches for a better state of harmony, such as during jazz operation. The analogy between improvisation and optimization is as follows:

1. Each musician corresponds to each decision variable;

2. Musical instruments pitch range corresponds to the decision variables value range;

3. Musical harmony at a certain time corresponds to the solution vector at a certain iteration;

4. Audiences aesthetics corresponds to the objective function.

The sound for better aesthetic quality can be improved through practice after practice, just as the values for better objective function evaluation or solution vector can be improved iteration by iteration. Musical performance and optimization processes are shown in Table 5.1 [106].

Table 5.1: Analogy between Musical Performance and Optimization Process

Comparison Factor	**Performance Process**	**Optimization Process**
Best State	Fantastic Harmony	Global Optimum
Estimated by	Aesthetic Standard	Objective Function
Estimated with	Pitches of instruments	Values of Variables
Process Unit	Each Practice	Each Iteration

5.2.1 Structure of Harmony Search Algorithm

The harmony search algorithm idealizes the improvisation process by a skilled musician. When a musician is improvising, the musician has three possible choices [105]:

I. Play any famous piece of music (a series of pitches in harmony) exactly from the memory which corresponds to harmony memory.

II. Play something similar to a known piece (thus adjusting the pitch slightly) which corresponds to pitch Adjusting.

III. Compose new or random notes which corresponds to randomization.

State of perfect harmony is reached by adjusting a combination of above three parameters.

5.2.2 Characteristics of Harmony Search Algorithm

Harmony search algorithm has several characteristics that makes it one of the most important meta-heuristic algorithms and distinguish it from other meta-heuristics. Some of these includes,

- generation of a new vector after considering all the existing vectors, rather than considering only two parent vectors;
- independent consideration for each of decision variable in a vector;
- the consideration of continuous decision variable values without any loss of precision;
- it does not require decimal-binary conversions or a fixed number (2n) of decision variable values; and
- it does not require suitable starting values of the decision variables nor does it require complex derivatives as in gradient-based methods.

Based on the above characteristics, HS algorithm has four main steps illustrated as a flow-chart in Figure 5.1 and described as follows:

I. The parameters of the HS to be initialized are: Harmony Memory Size (HMS) (i.e. number of solution vectors in harmony memory); Harmony Memory Considering Rate (HMCR), where $HMCR \in [0,\ 1]$; Pitch Adjusting Rate (PAR), where $PAR \in [0,\ 1]$; Distance bandwidth (bw) and Stopping Criteria (i.e. number of improvisation (K)). More explanation of these parameters is given in the next steps.

II. Population of harmony memory by possible set of solutions or harmonies randomly. It can be a matrix or vector as :

$$HM = \begin{bmatrix} b_{1,1} & b_{1,2} & \cdots & b_{1,M} \\ b_{2,1} & b_{2,2} & \cdots & b_{2,M} \\ \vdots & \vdots & \cdots & \vdots \\ b_{HMS,1} & b_{HMS,2} & \cdots & b_{HMS,M} \end{bmatrix} \tag{5.1}$$

III. Harmony Improvisation by determining a new vector by adjusting three parameters i.e. memory consideration, pitch adjustment and random selection. Memory Consideration determines whether the new vector will be generated by harmony memory values or randomly.

IV. If the new Harmony is better than the worst fit harmony then it will be replaced by the new harmony, otherwise step 2 is repeated until the total number of function evaluations is reached.

5.2.3 Advantages of Harmony Search

The important strengths of HS are their improvisation operators, memory consideration; pitch adjustment; and random consideration, all of which play a major role in achieving the desired balance between the two major extremes for any optimization algorithm, which include intensification and diversification. Essentially, both pitch adjustment and random consideration are the key components of achieving desired diversification in HS. In random consideration, the new vector components are generated in random mode, thus having same level of efficiency as in other algorithms that work with randomization. This property allows HS to explore new regions that may not have been visited in the search space. While, the pitch adjustment adds a new way for HS to enhance its diversification ability by tuning the new vectors component within a given bandwidth. This is achieved by adding or subtracting a small random quantity to an existing component stored in HM. This operator, pitch adjustment, is a fine-tuning process of local solutions that ensures that good local solutions are retained, while it adds a new room for exploring new solutions. Further, the pitch adjustment operator can also be considered as a mechanism to support the intensification of HS through controlling the probability of PAR. The intensification in the HS algorithm is represented by the third HS operator, memory consideration. A high harmony acceptance rate means that good solutions from the history/memory are more likely to be selected or inherited. This is equivalent to a certain degree of elitism. Obviously, if the acceptance rate is too low, solutions will converge more slowly. Finally, the structure of the HS algorithm is relatively easy. This advantage makes it very flexible to combine HS with other meta-heuristic algorithms.

5.3 PAPR minimization using Improved Harmony Search Algorithm

This section describes the improved harmony search algorithm and its performance for PTS technique. First, a brief overview of the harmony search based PTS (HS-PTS) is provided and stated here. Harmony Search based PTS Algorithm was discussed by Kermani et al in [17, 108].

5.3.1 Harmony search based PTS algorithm (HS-PTS)

HS-PTS algorithm has five main steps illustrated as a flow- chart in Figure 5.1 and described as follows:

Step 1: **Initialize the problem and HS parameters**:
In the first step, the optimization problem is specified as the minimum PAPR for PTS scheme is relative to the problem is initially modeled as:

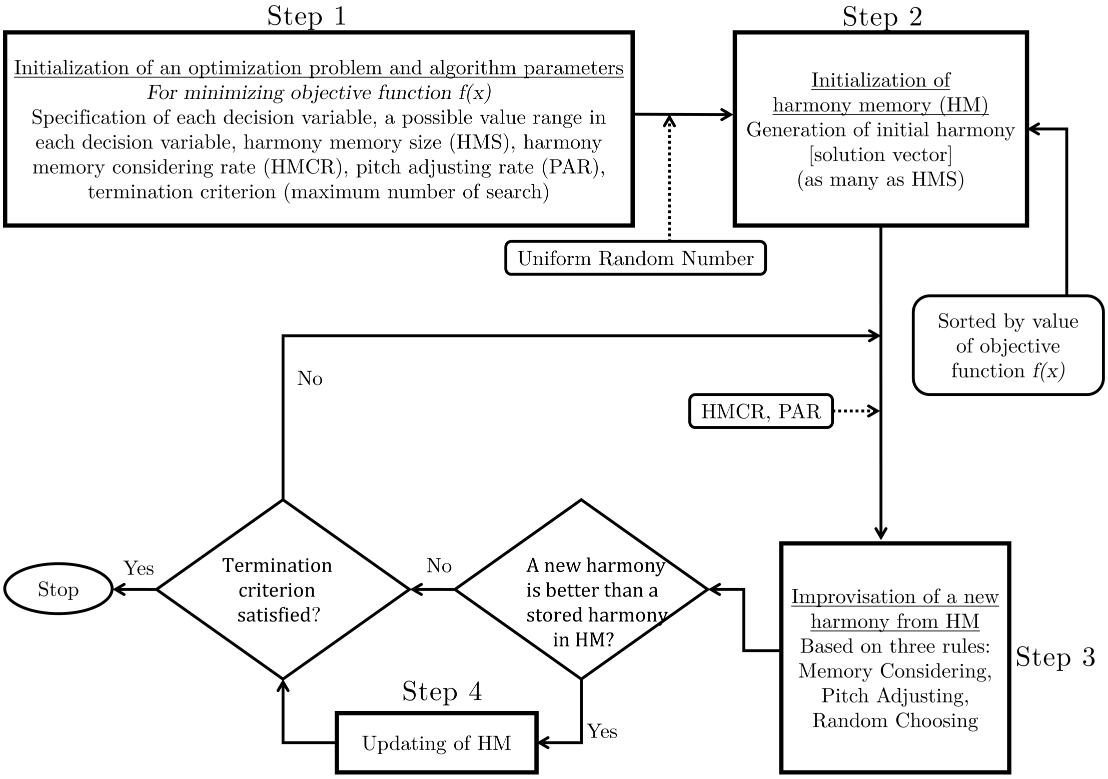


Figure 5.1: Flow chart of Harmony Search algorithm

Minimize

$$f(b) = \frac{\max\left[|x(b)|^2\right]}{E\left[|x(b)|^2\right]} \tag{5.2}$$

subject to

$$b \in \left\{e^{j\phi_m}\right\}^M \tag{5.3}$$

where $\phi_m \in \left\{\frac{2\pi k}{W} \,|k = 0, 1, ..., W-1\right\}$. The parameters of the HS algorithm required to solve the optimization problem are also specified in this step:

(a) The Harmony Memory Consideration Rate ($HMCR$), used in the improvisation process to determine whether the value of a decision variable is to be selected from the solutions stored in the harmony memory (HM).

(b) The Harmony Memory Size (HMS) is similar to the population size (G_n) in

Algorithm 3 Harmony Search based PTS (HS-PTS) Algorithm

Define $HMCR, PAR, HMS, bw$
$b_i = b_i^{min} + rand \in (0,1) \times (b_i^{max} - b_i^{min})$, where $i = 1, 2...HMS$; {generate HM solutions}
Calculate fitness function $f(b), b \in \left\{e^{j\phi_m}\right\}^M$
Define Maximum number of iterations (K)
$iter$=0
while $iter \leq K$ **do**
    for $i = 1, 2...HMS$
        if $rand \in (0,1) \leq HMCR$ **then**
            choose a value from HM
            $b_i \in [b_{i,1}, b_{i,2}, ...b_{i,HMS}]$; {memory consideration}
            if $rand \in (0,1) \leq PAR$ **then**
                $b_i = b_i^{min} + rand \in (0,1) \times (bw)$; {pitch adjustment}
            end if
        else
            choose a value from the possible solution collections:
            $b_i = b_i^{min} + rand \in (0,1) \times (b_i^{max} - b_i^{min})$; {random consideration}
        end if
    end for
    if $f(b) < f(b_{worst})$ **then**
        include b to HM
        Exclude (b_{worst}) from HM
        accept the new phase factor and replace the worst one in HM with it
    end if
    $iter = iter + 1$
end while
best = find the current best solution

the Cuckoo Search algorithm.

(c) The Pitch Adjustment Rate (PAR), decides whether the decision variables are to be adjusted to a neighboring value.

(d) The distance bandwidth (bw), determines the distance of adjustment in the pitch adjustment operator.

(e) The Number of Improvisations (NI) corresponds to the number of iterations

(K).

These parameters will be explained in more detail in the next steps. Note that the $HMCR$ and PAR are the two parameters which control the three operators of HS algorithm (i.e., (i) memory consideration is controlled by $HMCR$, (ii) random consideration is controlled by $1 - HMCR$, and (iii) pitch adjustment is controlled by PAR).

Step 2: **Initialize the harmony memory**

The harmony memory (HM) is an augmented matrix of size $M\ times HMS$ which contains sets of solution vectors determined by HMS (see (5.1)). In this step, these vectors are randomly generated as follows:

$$b_i = b_i^{min} + rand \in (0,1) \times (b_i^{max} - b_i^{min}) \tag{5.4}$$

where b_i^{min} and b_i^{max} are the lower and upper boundaries of the search space, respectively; and $rand \in (0,1)$ is a random real number in the range [0, 1]. The generated solutions are stored in HM in ascending order according to their objective function values.

Step 3: **Improvise a new harmony**

In this step, the HS algorithm will generate (improvise) a new harmony vector from scratch, $b \in \left\{e^{j\phi_m}\right\}^M$, based on three operators: (i) memory consideration, (ii) random consideration, and (iii) pitch adjustment.

i. **Memory consideration**

   In memory consideration, the value of the first decision variable b'_1 is randomly selected from the historical values, $b_i \in [b_{i,1}, b_{i,2}, ..., b_{i,HMS}]$, stored in HM vectors. Values of the other decision variables, $(b'_2, b'_3, \cdots, b'_M)$, are sequentially selected in the same manner with probability (w.p.) $HMCR$ where $HMCR \in (0,1)$. It is worth noting that the selection scheme in memory consideration is random and that the natural selection principle is not used.

ii. **Random consideration**

Decision variables that are not assigned with values according to memory consideration are randomly assigned according to their possible range by random consideration with a probability of $(1 - HMCR)$ as follows:

$$b'_i \leftarrow \begin{cases} b'_i \in \{b_{i,1}, b_{i,2}, \cdots, b_{i,HMS}\} & \text{with probability } HMCR \\ b'_i \in \left\{e^{j\phi_m}\right\}^M & \text{with probability } (1 - HMCR) \end{cases} \tag{5.5}$$

iii. **Pitch adjustment**

Each decision variable b'_i of a new harmony vector, $(b'_1, b'_2, b'_3 \cdots, b'_M)$, that has been assigned a value by memory considerations is pitch adjusted with the probability of PAR where $PAR \in (0, 1)$ as follows:

$$\text{Pitch adjusting decision for } b'_i \leftarrow \begin{cases} \text{Yes} & \text{with probability } PAR \\ \text{No} & \text{with probability } (1 - PAR) \end{cases} \tag{5.6}$$

If the pitch adjustment decision for b'_i is Yes, the value of b'_i is modified to its neighboring value as follows:

$$b'_i = b_i^{min} + rand \in (0, 1) \times (bw) \tag{5.7}$$

Step 4: **Update the harmony memory**

If the new harmony vector, $(b'_1, b'_2, b'_3 \cdots, b'_M)$, is better than the worst harmony (b_{worst}) stored in HM in terms of the objective function value (i.e., $(b_{worst}) = (b_{HMS})$ in case HM is sorted), the new harmony vector is included to the HM, and the worst harmony vector is excluded from the HM. This is a greedy selection scheme where the principle of natural selection is applied.

Step 5: **Check the stop criterion**

Step 3 and step 4 of HS algorithm are repeated until the stop criterion (maximum number of iterations) is met. This is specified by K.

Harmony search algorithm received attention of many researchers to solve variety of optimization problems in engineering and computer science areas [109]. Harmony Search based PTS Algorithm was presented by Kermani et al in [17,108].Consequently, the interest in this algorithm led researchers to improve performance in line with the requirements of problems that are to be solved [110,111]. The proper selection of HS parameter values is considered as one of the challenging task for HS algorithm as in other meta-heuristic algorithms. This difficulty is a result of different reasons, and the most important one is the absence of general rules governing this aspect. Actually, initializing parameter is problem dependent and therefore the experimental trials are the only guide to the best values. However, this matter guides the research into new variants of HS. These variants are based on adding some extra components or concepts to make part of these parameters dynamically adapted. These includes Improved Harmony Search (IHS), Global-best Harmony Search (GHS), Differential-evolution Harmony Search (DHS), Novel Global Harmony Search (NGHS) etc. Various variants of harmony search algorithms have been investigated in literature [108, 109, 112, 113].

5.3.2 Improved Harmony Search Algorithm for PTS

Performance of any metaheuristic algorithm like harmony search depends upon two factors: exploration and exploitation. Optimal and balanced combination of these two contradicting factors determine the efficiency of the algorithm. An improvement to HS was reported by Mahdavi et al that is termed as Improved Harmony Search (IHS) algorithm [104].

The $HMCR$ and PAR parameters introduced in Step 3 of HS-PTS algorithm help to find globally and locally improved solutions, respectively. PAR and bw in the HS-PTS algorithm are very important parameters in fine-tuning of optimized solution vectors, and can be potentially useful in adjusting convergence rate of algorithm to obtain an optimal solution. So fine adjustment of these parameters are of great importance. The traditional HS-PTS algorithm uses a fixed value for both PAR and bw. In the HS-PTS method PAR and bw values are adjusted in the initialization step (Step 1) and cannot be changed during new generations. The key difference between IHS-PTS and traditional HS-PTS method is in the way of adjusting PAR and bw. To improve the performance of the HS algorithm and eliminate the drawbacks with fixed values of PAR and bw, IHS-PTS algorithm uses variables PAR and bw in improvisation step (Step 3).

Improved Harmony Search Algorithm attempts to enhance accuracy and convergence rate of harmony search by adjusting Pitch Adjusting Rate PAR and distance bandwidth bw values. The PAR value is linearly increased in each iteration of HS by using the following relationship:

$$PAR(k) = PAR_{\min} + \left(\frac{PAR_{\max} - PAR_{\min}}{K}\right) k \tag{5.8}$$

The bandwidth (bw) value is exponentially reduced in each iteration of HS by using the following equation:

$$bw(k) = bw_{\max} \exp\left(\frac{\ln\left(bw_{\min}/bw_{\max}\right)}{K}\right) k \tag{5.9}$$

Where k and K represents the current number of improvisations and maximum number of improvisations respectively. As PAR and bw is initialized and fixed in traditional Harmony Search Algorithm, it provides inferior performance as well as more number of iterations are needed for finding the optimal Solution. Adjusting PAR and bw in each improvisation step delivers better convergence rate leading to optimal solutions. This gives suboptimal solution to enhance the performance of the basic HS algorithm.

Based on the above analysis, the basic steps of IHS-PTS technique can be summarized as the pseudo code shown in Algorithm 4.

Algorithm 4 Improved Harmony Search based PTS Algorithm (IHS-PTS)

Define $HMS, HMCR, K, PAR_{min}, PAR_{max}, bw_{min}, bw_{max}$
$b_i = b_i^{min} + rand \in (0,1) \times (b_i^{max} - b_i^{min})$, where $i = 1, 2...HMS$;
Calculate the Objective function $f(b), b \in \left\{e^{j\phi_m}\right\}^M$
Define Maximum number of iterations (K)
Initialize HM
for $b_i = 1 : HMS$ **do**
  Improvise new HM
  for $iteration \leq K$ **do**
    for $b_i \leq$ no. of variable **do**
      $PAR(k) = PAR_{\min} + \left(\frac{PAR_{\max} - PAR_{\min}}{K}\right) k$
      $bw(k) = bw_{\max} \exp\left(\frac{\ln(bw_{\min}/bw_{\max})}{K}\right) k$
      for (all variable) **do**
        if $rand \in (0,1) \leq HMCR$ **then**
          choose a value from HM
          $b_i \in [b_{i,1}, b_{i,2}, ...b_{i,HMS}]$;
          if $rand \in (0,1) \leq PAR$ **then**
            $b_i = b_i^{min} + rand \in (0,1) \times (bw)$;
          end if
        else
          (Choose a random value of variable)
          $b_i = b_i^{min} + rand \in (0,1) \times (b_i^{max} - b_i^{min})$
        end if
      end for
      if new solution $\leq$ worst solution **then**
        accept the new harmony and replace the worst in HM
      end if
    end for
  end for
end for
best = best current solution

5.4 Simulation Results and Discussions

To evaluate the performance of IHS-PTS algorithm for OFDM PAPR reduction, various simulations were conducted. To generate the CCDF of the PAPR, 10,000 symbols of 16-QAM, OFDM symbols were generated and the transmitted signal was oversampled by a factor of 4 for obtaining accurate PAPR value. The performance of IHS-PTS was compared with conventional PTS and other PAPR reduction schemes.

5.4.1 Variation in parameteric constraints of IHS-PTS algorithm

Harmony Search based PTS (HS-PTS) was presented by Kermani et al. [17, 108], in which the value of $HMCR$ and PAR were considered as 0.95 and 0.05 respectively. Mahdavi et al proposed the Improved Harmony Search (IHS) algorithm [104] and several examples for various problems analyzed the methods for selection of the parameter. In the majority of applications, parameters are set by trial and error for finding optimal performance of algorithm. In this work, simulations were performed to analyze the performance of $PAR_{\min}$, $PAR_{\max}$, $bw_{\min}$ and $bw_{\max}$ for IHS-PTS optimization. These parameters are presented in Table 5.2 and 5.3. Table 5.2 represents the PAPR value after simulation with variation in $PAR_{\min}$ and $PAR_{\max}$ and considering the value of $HMCR$=0.95, G_n=16, $bw_{\min}$=0.2 and $bw_{\max}$=0.5. Following this, Table 5.3 shows the simulation results with variation in $bw_{\min}$ and $bw_{\max}$ after considering the value of $HMCR$=0.95, G_n=16, $PAR_{\min}$=0.3 and $PAR_{\max}$=0.9. It can be seen from the results that $PAR_{\min}$=0.3, $PAR_{\max}$=0.9, $bw_{\min}$=0.2 and $bw_{\max}$=0.5 provides optimum values for IHS-PTS optimization. Selection of G_n, maximum number of iterations (K) has been analyzed in next section. In these simulations, $G_n = 16$ and $K = 10$ was used.

For HS-PTS algorithm, the parameters affecting performance include as: harmony memory size G_n which was set to 16, harmony memory consideration rate ($HMCR$) set to 0.95, pitch adjustment rate (PAR) set to 0.05 and the bandwidth of adjustment (bw) set to 0.2. The total number of iterations K was 10. To

Table 5.2: Results by IHS-PTS for PAPR values with different values of PAR

$HMCR$	$PAR_{\min}$	$PAR_{\max}$	G_n	$bw_{\min}$	$bw_{\max}$	K	PAPR (dB)
0.95	0.1	0.9	16	0.2	0.5	10	7.2
0.95	0.2	0.9	16	0.2	0.5	10	6.9
0.95	0.3	0.9	16	0.2	0.5	10	6.8
0.95	0.4	0.9	16	0.2	0.5	10	7.1
0.95	0.5	0.9	16	0.2	0.5	10	7.3
0.95	0.6	0.9	16	0.2	0.5	10	7.4
0.95	0.7	0.9	16	0.2	0.5	10	7.7
0.95	0.8	0.9	16	0.2	0.5	10	8.0

Table 5.3: Results by IHS-PTS for PAPR values with different values of bw

$HMCR$	$PAR_{\min}$	$PAR_{\max}$	G_n	$bw_{\min}$	$bw_{\max}$	K	PAPR (dB)
0.95	0.3	0.9	16	0.1	0.5	10	6.8
0.95	0.3	0.9	16	0.2	0.5	10	6.8
0.95	0.3	0.9	16	0.3	0.5	10	7.1
0.95	0.3	0.9	16	0.4	0.5	10	7.5
0.95	0.3	0.9	16	0.1	1.0	10	7.3
0.95	0.3	0.9	16	0.2	1.0	10	7.4
0.95	0.3	0.9	16	0.3	1.0	10	7.8
0.95	0.3	0.9	16	0.4	1.0	10	8.0
0.95	0.3	0.9	16	0.1	4.0	10	8.1
0.95	0.3	0.9	16	0.2	4.0	10	7.4
0.95	0.3	0.9	16	0.3	4.0	10	7.7
0.95	0.3	0.9	16	0.4	4.0	10	8.2

improve the performance of algorithm, improved version of harmony search algorithm called Improved Harmony Search (IHS) was applied, in which PAR and bw were dynamically updated. When this algorithm was used with PTS (IHS-PTS), the PAPR performance for OFDM signal was seen to be improved. For simulation, the minimum and maximum value of PAR and bandwidth were considered as $PAR_{\min}$=0.3, $PAR_{\max}$=0.9, $bw_{\min}$=0.2 and $bw_{\max}$=0.5 respectively. Both values

Table 5.4: IHS-PTS Simulation Parameters

Simulation Parameters	**Type/Value**
Number of sub-carriers (N)	128, 256, 512
Number of sub-blocks (M)	4, 8, 16
OFDM Blocks	10,000
Oversampling Factor (L)	4
Bits per symbol (b)	4
Phase rotation factors (W)	$\{+1, -1\}$
PAPR in db	4 to 12
Harmony Memory Size (G_n)	16
Harmony Memory Consideration Rate ($HMCR$)	0.95
Pitch Adjustment Rate (PAR)	0.05
Bandwidth of Adjustment (bw)	0.2
Minimum value of PAR ($PAR_{\min}$)	0.3
Maximum value of PAR ($PAR_{\max}$)	0.9
Minimum value of bandwidth ($bw_{\min}$)	0.2
Maximum value of bandwidth ($bw_{\max}$)	0.5
Constellation Size	16-QAM
No. of iterations (K)	5,10,20

were updated by using (5.8) and (5.9). When these methods were used to optimize the phase factor in IPTS based PAPR reduction, the PAPR was observed to be improved in each case (reduction in PAPR).

5.4.1.1 Variation in number of iterations K

At first,the effect on number of iteration K was analyzed. Figure 5.2 compares the CCDF vs PAPR performance of IHS-PTS technique as function of various iterations K in a system with 16-QAM modulation, N= 256, M= 8 and W=2. When the number of iterations K are 10, then PAPR of original OFDM signal and IPTS are 11.1 dB and 8.2 dB respectively. After applying HS-PTS and IHS-PTS, the PAPR reduced to 7.3 dB and 6.8 dB respectively. When the number of iterations K were enhanced to 20, then PAPR of HS-PTS and IHS-PTS were observed to be 7.2 dB and 6.6 dB respectively. In continuation with this, when simulations

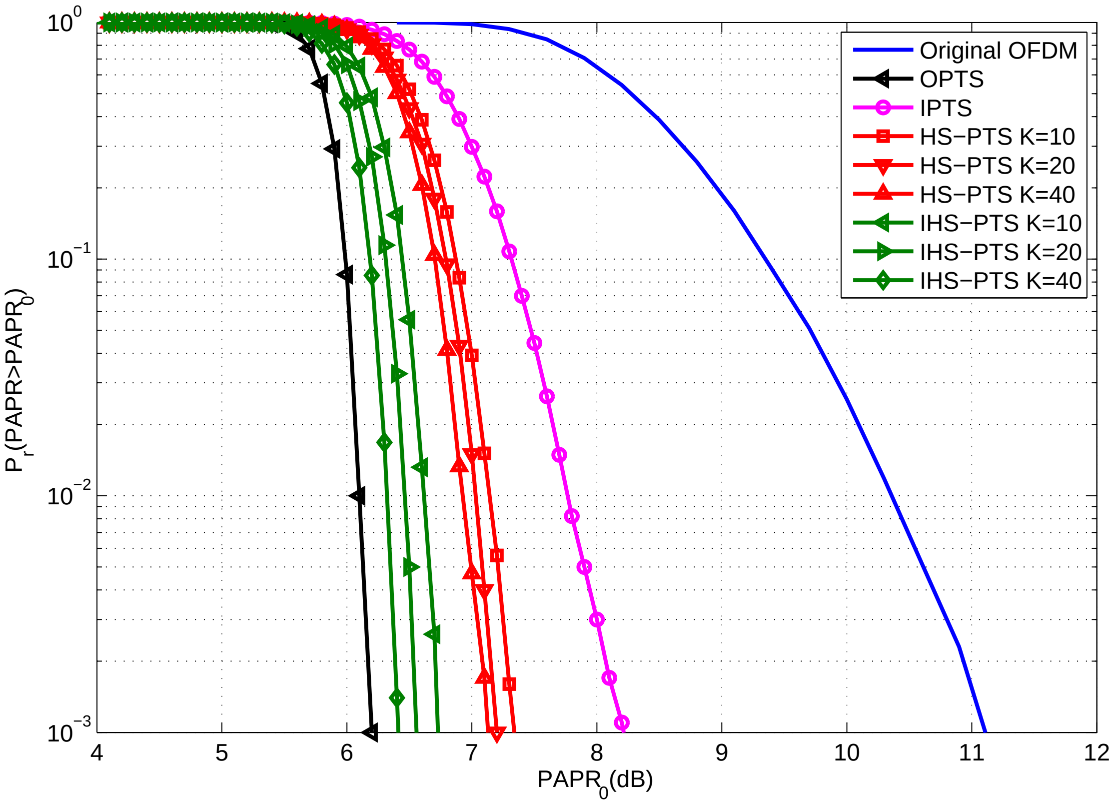


Figure 5.2: CCDF vs PAPR performance of IHS-PTS technique for different iterations, when N= 256, M=8, W=2, HMS=16

were conducted for 40 iterations, the PAPR of HS-PTS and IHS-PTS were observed to be 7.1 dB and 6.4 dB respectively at CCDF of 10^{-3}. As the number of iterations was increased, the PAPR improved. However, increase in iterations enhance processing time, since with larger number of iterations, the number of function evaluation leading computation complexity also increases. Hence, it can be seen that the optimization based PTS schemes delivers desirable trade-off between the PAPR performance and computational complexity. All these schemes provide PAPR performance between IPTS and OPTS.

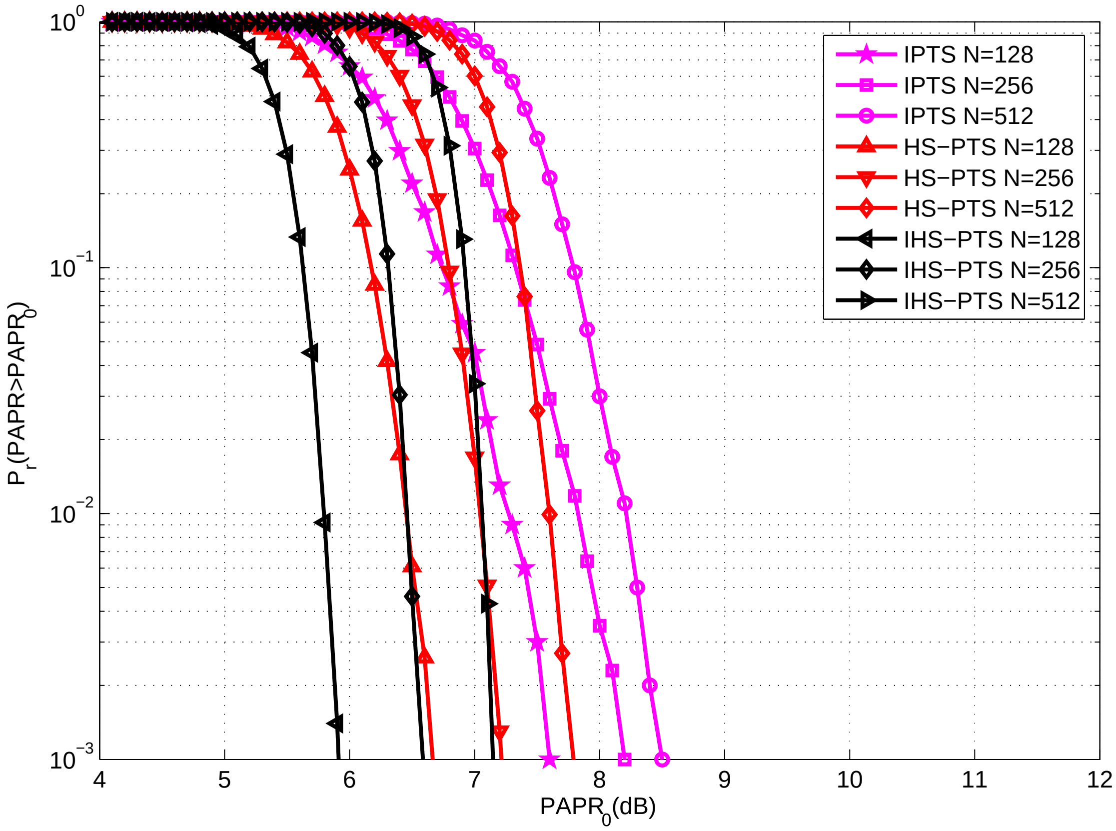


Figure 5.3: CCDF vs PAPR performance of IHS-PTS technique for N= 128, 256, 512 sub-carriers, when M=8, W=2, HMS=16, K=10

5.4.2 Study on the effects of OFDM system parameters on PAPR

Sensitivity of the algorithmic parameters were discussed in the previous subsection. Following this, the performance of IHS-PTS has been evaluated for different number of parameters.

5.4.2.1 Effect of variation in sub-carrier N

The performance of the algorithm was evaluated for different sub-carrier considerations. In Figure 5.3, simulation results of CCDF vs PAPR performance of 16-QAM IHS-PTS system for different number of sub-carriers are presented, when

M=8 and W=2. Simulation results are presented for original OFDM, IPTS, HS-PTS and IHS-PTS algorithms. Uniformly distributed random variable were used for phase weight factor b . From results, it can be observed that for a given CCDF, increase in sub-carriers enhances PAPR. As the numbers of sub-carriers are increased, there was improvement in PAPR performance. In simulation results, when N= 128, M= 8 and W=2, the PAPR achieved with IPTS scheme is approximately 7.6 dB. After applying HS-PTS and IHS-PTS, PAPR of 7.8 dB and 7.1 dB were observed respectively for CCDF of 10^{-3}. In continuation with this, when N= 256, M= 8 and W=2, the PAPR of IPTS technique is around 8.2 dB. After applying HS-PTS and IHS-PTS, PAPR observed were 7.2 dB and 7.1 dB respectively with CCDF of 10^{-3}. However with N= 512 sub-carriers, the PAPR of IPTS are approximately 8.5 dB. The PAPR of OFDM signal after the HS-PTS and IHS-PTS are 7.8 dB and 7.1 dB respectively with CCDF of 10^{-3}. So, it is observed that PAPR values are dependent on number of sub-carriers used for OFDM generation and, the optimization algorithms based PTS gives the improvement in PAPR performance in each case. From above the descriptions, we can see that IHS- PTS is an effective technique for reducing the PAPR of OFDM system, even with large number of sub-carriers. It is also important to note that for OFDM signals with large number of sub-blocks, OPTS could not be implemented due to extensive computational complexity.

5.4.2.2 Effect of variation in sub-block M

Figure 5.4 illustrates CCDF vs PAPR performance of 16-QAM IHS-PTS system for different number of sub-blocks. It can be seen that, the PAPR of original OFDM signal is around 11 dB at CCDF= 10^{-3}. PAPR can be reduce to 8.8 dB with CCDF of 10^{-3} for M=4 sub-blocks using IPTS with N= 256 and W=2. After applying HS-PTS and IHS-PTS technique, the PAPR observed to be around 7.5

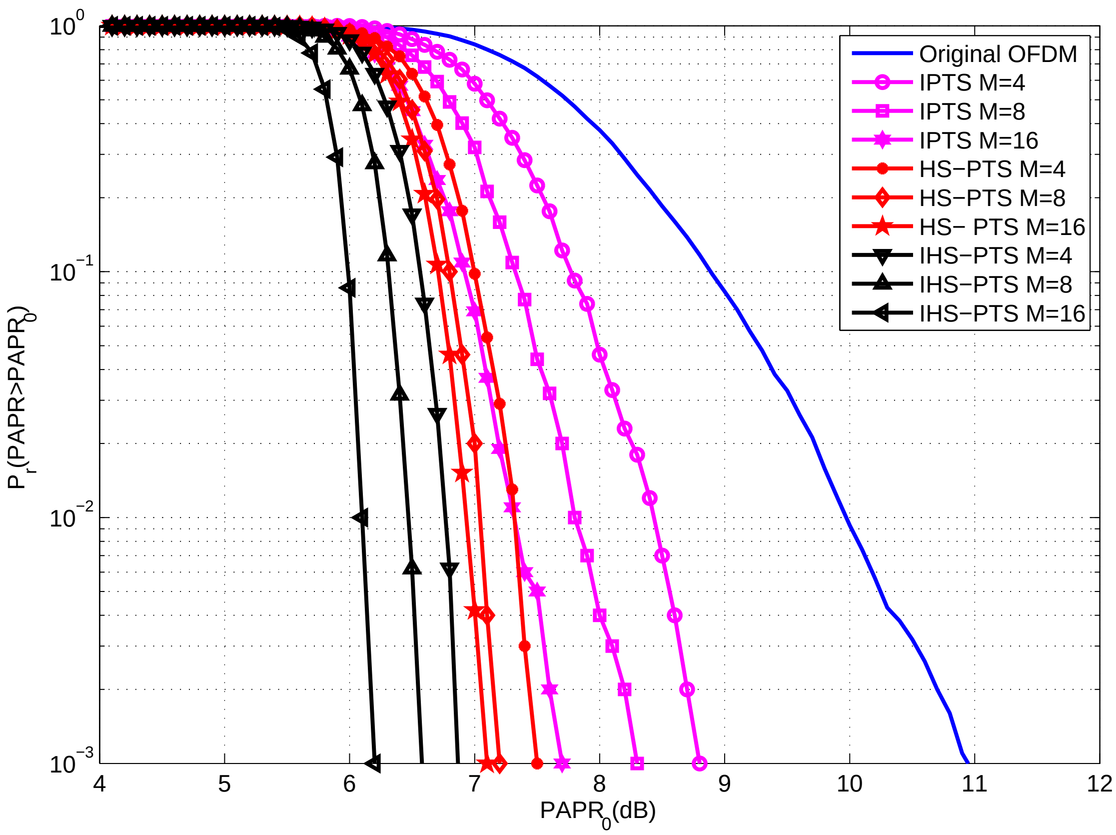


Figure 5.4: CCDF vs PAPR performance of IHS-PTS technique for M= 4, 8, 16 sub-blocks, when N= 256, W=2, HMS=16, K=10

dB and 6.9 dB respectively. So, among all these three schemes, IHS-PTS provides superior performance in reducing PAPR of the OFDM signal. Next simulation was performed for M= 8 and 16 sub-blocks. It is seen that increase in number of sub-bloks improves the performance. It can also be seen that, IHS-PTS scheme provides reduced PAPR as compared to the HS-PTS algorithm. For M=8, the PAPR of 8.3 dB was observed with IPTS. When the HS-PTS and IHS-PTS show a PAPR of 7.2 dB and 6.6 dB respectively. Similarly for M=16, the PAPR of IPTS is around 7.7 dB, Where as, with HS-PTS and IHS-PTS PAPR achieved is 7.1 dB and 6.2 dB respectively. Hence it is observed that the IHS-PTS scheme performs better than the other two methods i.e. IPTS and HS-PTS for similar

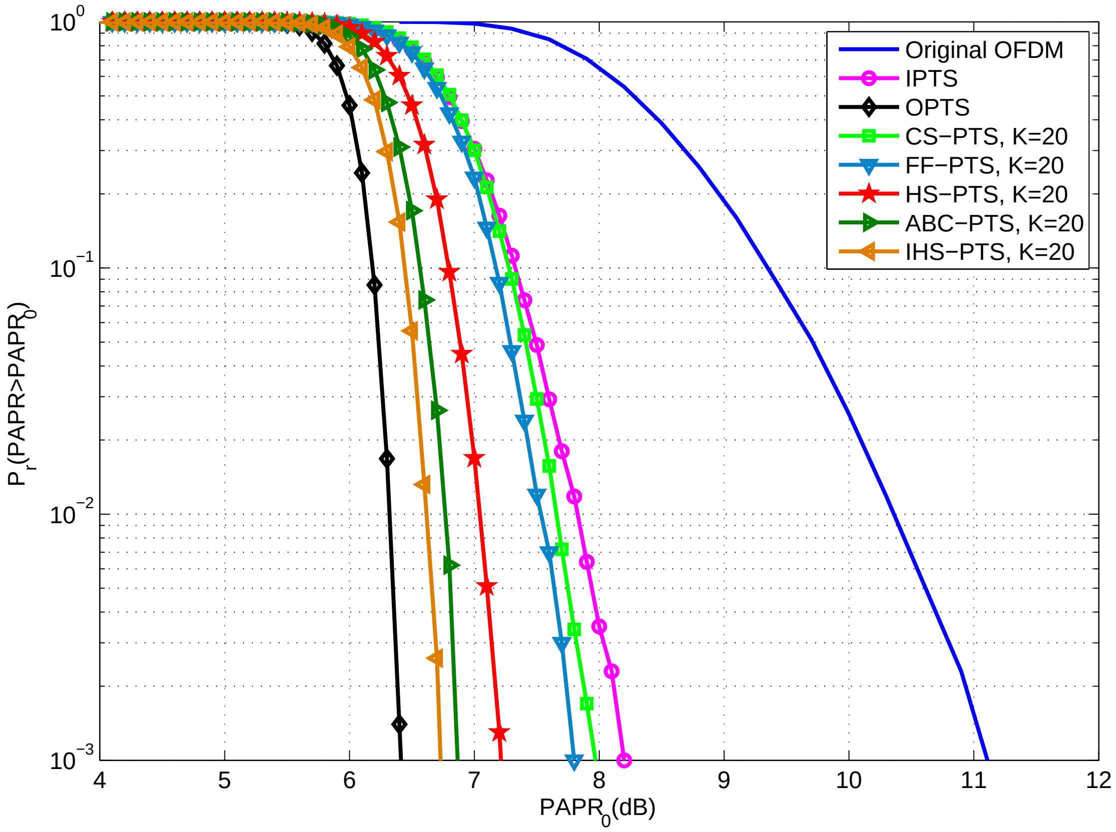


Figure 5.5: Comparison of CCDF vs PAPR performance of IHS-PTS system with different methods for N= 256, when M=8, W=2, HMS=16

conditions. Moreover, it can also be observed that, as the number of sub-blocks and the set of phase weighting factor are increased, PAPR reduction improves but, the processing time also increases because of complexity involved.

In order to investigate the performance of proposed algorithm with few state of the art techniques, the performance were compared with ABC-PTS [15] and HS-PTS [108]. Figure 5.5, presents the PAPR performance of the IHS-PTS with the OPTS [36], IPTS [9], ABC-PTS [15], HS-PTS [108], FF-PTS and CS-PTS for similar number of iterations. The performance of IHS-PTS with maximum iteration number $K = 20$ with sub-blocks $M = 8$ were generated by random partition with N= 256 and W=2 was presented at Figure 5.5. When $Pr(PAPR >$

$PAPR_0) = 10^{-3}$, the PAPR of the original OFDM is 11.1 dB. The PAPR by the IPTS [9] is 8.2 dB providing a 2.9dB PAPR gain. Compared to the PAPR achieved by OPTS is approximately 6.45 dB, a PAPR improvement of 4.65dB. Using the IHS-PTS with K =20, the PAPR is seen reduce to 6.7 dB constituting a 4.4dB gain. The PAPR achieved by ABC-PTS with 20 iterations is approximately 6.8 dB and HS-PTS is 7.2 dB. In continuation with this the PAPR of CS-PTS and FF-PTS schemes is approximately 7.9 dB and 7.8 dB respectively. It demonstrates that as compared to the OPTS, the PAPR reduction by the IHS-PTS algorithm has a performance penalty of less than 1 dB. Performance of IHS-PTS is superior than other optimization techniques. The computational complexities issues are analyzed in next subsection.

5.4.2.3 IHS-PTS performance for different modulation formats

The effect of modulation formats on PAPR was next analyzed for IHS-PTS algorithm. Figure 5.6 presents the PAPR performance of HS-PTS and IHS-PTS scheme for different modulation orders like QPSK, 8-QAM, 16-QAM, 32-QAM and 64-QAM. Simulation parameters were taken as M=8 sub-blocks, N=256 sub-carriers, W=2, K=10 iterations. The population size/ generations were considered from 10 to 20 only. It can be seen from results that IHS-PTS provides linear performance for different modulation formats. At G_n=20, PAPR performance of IHS-PTS scheme approximately close to OPTS, but at the cost of higher complexity. So, a trade-off between PAPR performance and complexity calculation in terms of population size is required for implementation.

5.4.2.4 IHS-PTS performance with varying number of sub-carriers

The summarized results presented in Figure 5.7 shows the 16-QAM HS-PTS and IHS-PTS performance for different number of sub-carriers varied in the range 32 to 512, when M=8, W=2, K=10. It can be seen from the graph that the perfor-

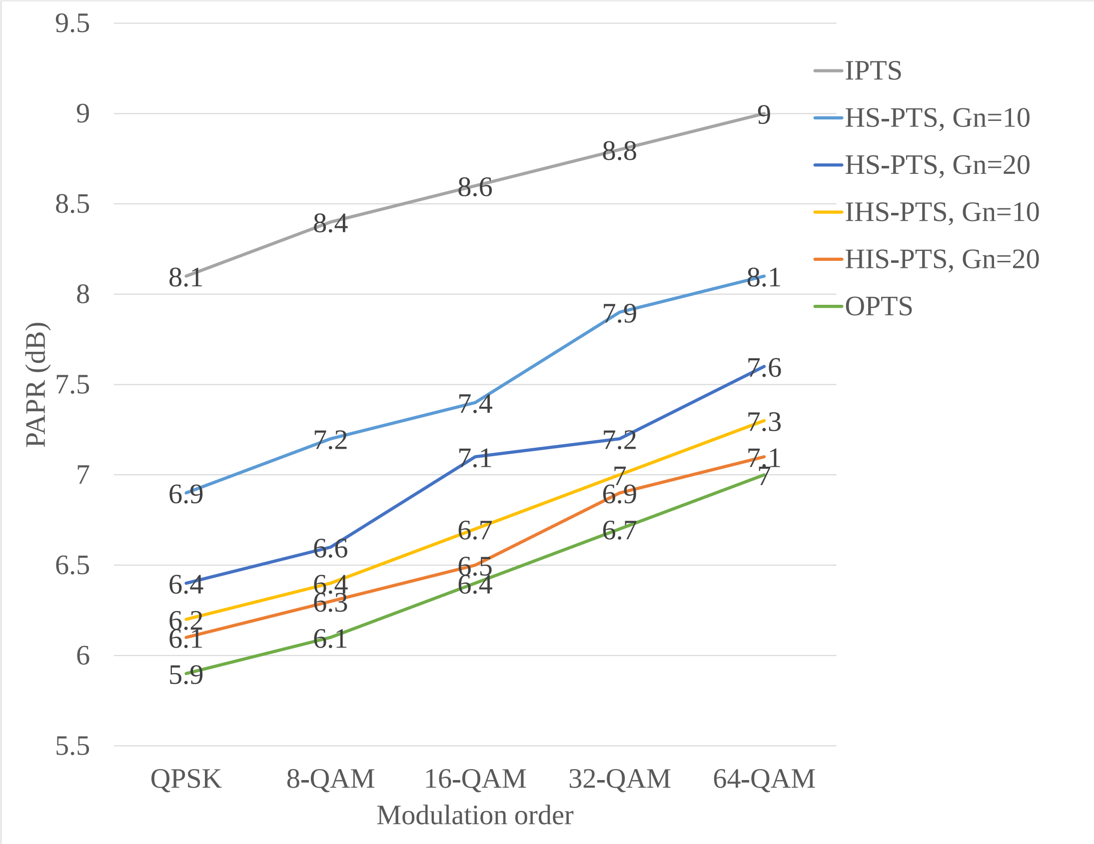


Figure 5.6: IHS-PTS performance for different modulation formats

mance of IHS-PTS scheme was very close to OPTS at very less number of generations/population size i.e. G_n=20. It is also clear from the results that performance of the PTS technique degrades with the increase in number of sub-carriers.

5.4.3 Analysis of the Computational Complexity

Following the IHS based PAPR performance, the computational complexity is discussed here. Table 5.5 presents the CCDF vs PAPR Performance and the associated computational complexity analysis for 16-QAM OFDM-PTS Technique with various optimization methods like CS-PTS, FF-PTS, HS-PTS and IHS-PTS with different number of sub-blocks M=8 and 16 are summarized.

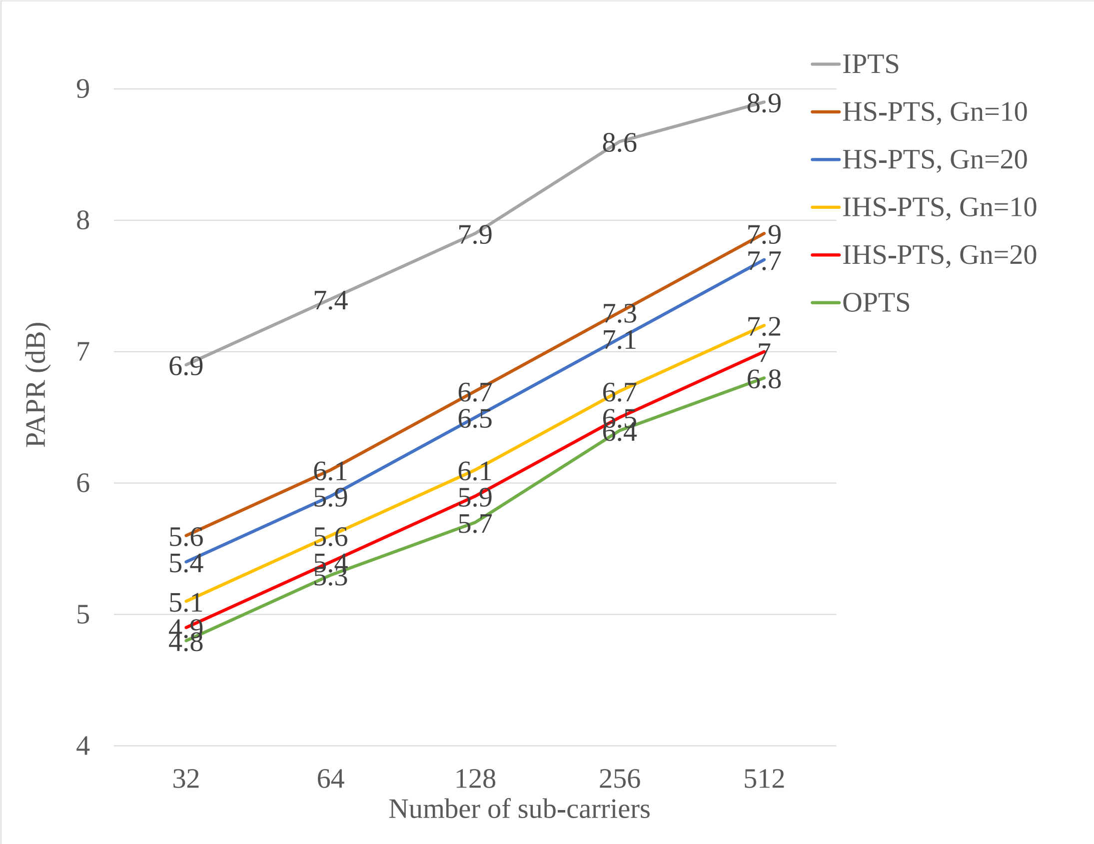


Figure 5.7: IHS-PTS performance for different number of sub-carriers

For harmony search method, the searching complexity is given by number of sub-blocks M multiplied by number of iterations K and number of phase vector W. When the number of sub-blocks M is 8 and number of iterations K is 10 with phase vector W =2, then searching complexity is 160, which is similar as the complexity of OPTS i.e. 128. For improved harmony search based PTS, the PAPR performance is superior with same computational complexity as compared with HS-PTS. The FF-PTS uses searching complexity given by square of number of fireflies G_n multiplied by number of iterations K.

From this table, it can be observed that partial transmit sequence method with various optimization techniques reduces the PAPR of original OFDM signal

Table 5.5: Comparison of computational complexity of different optimization algorithms at CCDF = 10^{-3}, Modulation format : 16-QAM

Methods	Combinations	Computational Complexity	PAPR (db)
OPTS	M=8, N=256, W=2	(W^{M-1})= 128	6.5
	M=16, N=256, W=2	(W^{M-1})= 32768	6.1
IPTS	M=8, N=256, W=2	$(W \times M)$= 16	8.6
	M=16, N=256, W=2	$(W \times M)$= 32	7.6
FF-PTS	M=8, N=256, W=2, G_n=10, K=10	$(G_n{}^2K)$= 1000	7.8
	M=16, N=256, W=2, G_n=10, K=10	$(G_n{}^2K)$ = 1000	7.2
CS-PTS	M=8, N=256, W=2, G_n=16, K=10	$(G_n * (G_n + 1))/2$= 136	7.9
	M=16, N=256, W=2, G_n=16, K=10	$(G_n * (G_n + 1))/2$=136	7.4
HS-PTS	M=8, N=256, W=2, G_n=10, K=10	$M * W * K$= 160	7.3
	M=16, N=256, W=2, G_n=10, K=10	$M * W * K$= 320	7.1
IHS-PTS	M=8, N=256, W=2, G_n=10, K= 10	$M * W * K$= 160	6.6
	M= 16, N=256, W=2, G_n=10, K=10	$M * W * K$= 320	6.2

efficiently and improved performance has been observed, when the number of iterations of optimization method are increased. Increasing the number of iterations results in increment of searching complexity of phase factor too. In a nutshell, the performance of three techniques analyzed in this work is presented in Table 5.6. From above the descriptions, it can be seen that the IHS-PTS is an effective technique for reducing the PAPR of OFDM system.

5.5 Summary

In this chapter, a variant of harmony search algorithm i.e. improved harmony search has been applied to PTS algorithm (IHS-PTS) to search optimum com-

Table 5.6: Performance comparison of different optimization tecniques analyzed in this work

Methods	**Merits**	**Limitations**
FF-PTS	• Moderate structure • Can be trained with very small number of iterations i.e. K=10 • Increasing the number of sub-blocks provides consistent performance gain	• Requires tuning of large number of parameters termed as α, β, γ, K and G_n • Large value of α prevents the algorithm from converging too early, but at the cost of requiring more iterations to settle on a solution and limiting the system performance. • For large number of sub-blocks i.e. M=16, more OFDM samples are required
CS-PTS	• Very simple structure • Requires tuning of only 2 parameters ρ_d and G_n. • Only K=10 iterations are sufficient for training the network	• PAPR performance improves after increasing population size G_n but complexity will be increases gradually. • Performance of OPTS with 8 sub-blocks outperforms CS-PTS with 16 sub-blocks.
IHS-PTS	• Provides the best performance campared to other candidate algorithms • Lower computational complexity compared to FF-PTS and CS-PTS	• Complex structure • Needs large number of parameter adjustments

bination of phase factor for OFDM signals. Compared to the PAPR reduction optimization techniques like firefly algorithm, harmony search algorithm etc., the IHS-PTS algorithm provides improved PAPR performance. The performance of the algorithm can be summarized as:

- Simulation results indicate that IHS-PTS provides the best performance among the 3 candidate algorithms used.
- IHS-PTS is having complex structure and needs large number of parameter adjustments which includes $HMCR$, PAR_{min}, PAR_{max}, bw_{min}, bw_{max} and G_n.
- IHS-PTS has lower computational complexity compared to FF-PTS and CS-PTS. It also has lower complexity compared to OPTS with 16 sub-block. The complexity is higher than IPTS.
- Variation in number of sub-carriers and modulation format show similar trends in performance as compared to OPTS.

Simulation results show that it is an efficient and feasible method to provide better PAPR performance.

CHAPTER 6

Conclusions and Future Work

"I read what I write over and over and make corrections and improvements, until I reach the conclusion that the material deserves to stand on its own."

-Siegfried Lenz

Contents

6.1 Conclusions

Currently, OFDM is considered to be the de-facto standard for high-speed wired and wireless data communication. OFDM systems are inherently spectrally efficient. With demand for mobility in communication, power consumption and battery life have become a critical issue. Efficient PAPR reduction techniques improve power efficiency in mobile devices. Considering multiple candidate techniques, PTS seems to be the most promising, since it offers superior PAPR performance without data loss. However, PTS suffers from computational complexity, hence efficient implementation demands optimization of parameters leading to reduced performance..

Phase factor optimization in PTS has been attempted by researchers in the current decade. Some of the techniques that have been attempted includes Particle Swarm Optimization [13], Genetic Algorithm [14], Artificial Bee Colony Algorithm [15], Differential Evolution algorithm [16] and Harmony Search [17]. The work reported in this thesis investigated three new algorithms for the same problem. FF-PTS, CS-PTS and IHS-PTS based optimization techniques have been applied to the problem and performance investigated. Extensive simulation studies demonstrate the efficacy of the algorithm to the specified problem. These algorithms along with their performance have been discussed in detail in Chapter 3, 4 and 5. The optimum solution to PAPR reduction using PTS cab be achieved by using OPTS technique. Implementation of OPTS requires PAPR using sub-blocks. The complexity of the system is exponentially related to the number od sub-block used. It is feasible to implement OPTS using up to 8 sub-blocks. Sub-blocks beyond 8 i.e. 16, 32 and higher becomes impossible for practical implementation due to high computational complexity requirements which rise exponentially. The investigation made in the thesis and results there to can be summarized as under:

i. Among the three techniques investigated, the IHS-PTS provides the best performance in terms of PAPR. This has a performance close to OPTS. Considering the computational complexity, 16 sub-block IHS-PTS is feasible and is far less complex than OPTS. The system has a demerit of a large set of parameter adjustments. IHS-PTS in contrast to HS-PTS [17] provides the advantage of superior PAPR performance with same complexity.

ii. FF-PTS has a moderately complex structure but provides quick training. The performance is inferior to IHS-PTS and OPTS. The algorithm can be considered for implementation when the number of sub-block are higher. One of the major drawbacks of the scheme is that large value of α prevents the algorithm from converging too early at the cost of requiring more iterations to settle on a solution and limiting the system performance.

iii. CS-PTS has been inspired by CS algorithm. The algorithm is simple and requires training of few parameters only. Its qualitative performance is lowest among the three investigated techniques. It is attractive considering its computational complexity.

iv. All the techniques investigated provide uniform performance penalty with the change in modulation order and number of sub-carriers.

Although investigation of different optimization based techniques proposed in the literature and the work reported in the thesis shows that no single technique performs best, but under limiting circumstances and constraints some algorithm outperform others.

6.2 Scope for Future Work

In the present scenario, the PAPR problem is still a challenging issue mostly for the devices where the minimization of linear range of power amplifier is importance.

In this thesis, intelligent optimization algorithms with PTS technique to reduce the PAPR of OFDM system was presented. The proposed systems can be made more reliable by implementing techniques to recover the original signal in multipath environment without transmitting side information. Further enhancement on improving the complexity of the searching phase factors can be considered. Different optimized phase factors searching algorithm as presented in the literature survey chapter can be applied. Furthermore, window functions like Discrete Fourier Transform (DCT), Modified Bartlett-Hanning (MBH), Discrete Hartley Transform (DHT), Zadoff- Chu Transform (ZCT) etc can be applied to generate the precoding matrix. The proposed PAPR reduction technique can be applied with multiple input multiple output (MIMO) OFDM system.

The research work on different phase factor optimization techniques for PAPR reduction in OFDM systems are presented in the thesis can be further extended in following ways.

- Low complexity algorithm for evaluating the PAPR without IFFT.

  All sign-selection algorithms must calculate the time-domain samples and evaluate the PAPR of a large number of sign-sequence candidates. In this thesis, we proposed a fast algorithm to calculate the PAR without computing the magnitudes of all the time-domain samples. However, calculating the time-domain samples of a sign sequence still requires an IFFT. This requirement is costly because of the need to calculate a large number of candidates. A low complexity algorithm for evaluating the PAPR without IFFT would allow us to use more sign-sequence candidates to find a larger PAR reduction. Such an algorithm would also facilitate the use of clipping-based algorithms because they also require FFT/IFFT to compute the clipping noise in the time and frequency domains.

- Peak reduction criteria using a more appropriate measure than the PAPR.

  The purpose of peak reduction is to minimize the in-band distortion and out-of band radiation caused by the non-linearity of HPA. A small PAPR does not always imply a small in-band distortion and out-of-band radiation. Peak-reduction criteria using other measures observed that, when nonlinear amplification is allowed to some extent, the distribution of the envelope, rather than that of the PAPR, is a more relevant measure. A theoretical analysis and comparison of different peak-reduction criteria would help to develop more efficient peak-reduction algorithms.

- Bit loading algorithm for OFDM with PAPR optimization

  Bit loading is a technique used in multicarrier communication system (e.g. OFDM) to assign bits efficiently based on sub-channel quality. It allows more bits to be transmitted within higher quality sub-channel and less bits within lower quality sub-channels. Such kind of algorithms would provide better PAPR reduction with any heuristic optimization technique with trade-off in channel capacity and computational complexity.

Bibliography

[1] Ramjee Prasad, *OFDM for Wireless Communications Systems.* Artech House Universal Personal Communications Library, 2004.

[2] C. L. Henrik Schulze, *Theory and Applications of OFDM and CDMA: Wideband Wireless Communications.* John Wiley & Sons, Inc., 2005.

[3] K. Baybakov, T. Sviridova, M. Lobur, and R. Kohut, "Using OFDM for multiple access schemes in 4G communication systems," in *Proceedings of the 7th International Conference on the Experience of Designing and Application of CAD Systems in Microelectronics, CADSM 2003.*, pp. 572–573, Feb 2003.

[4] N. Marchetti, M. Rahman, S. Kumar, and R. Prasad, "OFDM: Principles and challenges," in *New Directions in Wireless Communications Research* (V. Tarokh, ed.), pp. 29–62, Springer US, 2009.

[5] H. Rohling, T. May, K. Bruninghaus, and R. Grunheid, "Broad-band OFDM radio transmission for multimedia applications," *Proceedings of the IEEE*, vol. 87, pp. 1778–1789, Oct 1999.

[6] Q. Han, X. Zeng, L. Zeng, and T. Wang, "Joint papr reduction method base on ace pocs and peak clipping," in *International Conference on Cyber-*

Enabled Distributed Computing and Knowledge Discovery (CyberC), 2010, pp. 371–375, Oct 2010.

[7] X. Li and L. Cimini, “Effects of clipping and filtering on the performance of OFDM,” in *Vehicular Technology Conference, 1997, IEEE 47th*, vol. 3, pp. 1634–1638 vol.3, May 1997.

[8] A. Jones, T. Wilkinson, and S. Barton, “Block coding scheme for reduction of peak to mean envelope power ratio of multicarrier transmission schemes,” *Electronics Letters*, vol. 30, pp. 2098–2099, Dec 1994.

[9] L. Cimini and N. Sollenberger, “Peak-to-Average Power Ratio reduction of an OFDM signal using partial transmit sequences,” *IEEE Communications Letters*, vol. 4, pp. 86–88, Mar. 2000.

[10] Y. L. Lee, Y. H. You, W. G. Jeon, J. H. Paik, and H. K. Song, “Peak-to-average power ratio in MIMO-OFDM systems using selective mapping,” *IEEE Communications Letters*, vol. 7, no. 12, pp. 575–577, 2003.

[11] S. H. Han and J. H. Lee, “An overview of peak-to-average power ratio reduction techniques for multicarrier transmission,” *IEEE Wireless Communications Magazine*, vol. 12, pp. 56–65, April 2005.

[12] J. Gao, J. Wang, B. Wang, and X. Song, “Minimizing PAPR of OFDM Signals Using Suboptimal Partial Transmit Sequences,” *IEEE International Conference on Information Science and Technology Wuhan, Hubei, China; March 23-25, 2012*, pp. 776–779, 2012.

[13] H. L. Hung, Y. F. Huang, C. M. Yeh, and T. H. Tan, “Performance of particle swarm optimization techniques on papr reduction for OFDM systems,” in

IEEE International Conference on Systems, Man and Cybernetics, 2008. SMC 2008., pp. 2390–2395, Oct 2008.

[14] M. Lixia, M. Murroni, and V. Popescu, "PAPR reduction in Multicarrier Modulations using Genetic Algorithms," in *12th International Conference on Optimization of Electrical and Electronic Equipment, OPTIM 2010*, pp. 938–942, 2010.

[15] Y. Wang, W. Chen, and C. Tellambura, "A PAPR Reduction Method Based on Artificial Bee Colony Algorithm for OFDM Signals," *IEEE Transactions on Wireless Communications*, vol. 9, pp. 2994–2999, October 2010.

[16] H. H. Y. Huang, H. L. Hung, and Y. F. Huang, "Peak-to-Average Power Ratio reduction in orthogonal frequency division multiplexing system using differential evolution-based partial transmit sequences scheme," *IET Communications*, vol. 6, no. 11, p. 1483, 2012.

[17] H. Salehinejad and S. Talebi, "PAPR Reduction of OFDM Signals by Novel Global Harmony Search in PTS Scheme," *International Journal of Digital Multimedia Broadcasting*, vol. 2012, 2012.

[18] B. Koussa, S. Bachir, C. Perrine, C. Duvanaud, and R. Vauzelle, "A comparison of several gradient based optimization algorithms for papr reduction in ofdm systems," in *2nd International Conference on Communications, Computing and Control Applications (CCCA), 2012*, pp. 1–6, Dec 2012.

[19] Z. Wang and G. Giannakis, "Wireless multicarrier communications," *IEEE Signal Processing Magazine*, vol. 17, pp. 29–48, May 2000.

[20] B. Saltzberg, "Performance of an Efficient Parallel Data Transmission System," *IEEE Transactions on Communication Technology*, vol. 15, pp. 805–811, December 1967.

[21] R. Chang and R. Gibby, "A Theoretical Study of Performance of an Orthogonal Multiplexing Data Transmission Scheme," *IEEE Transactions on Communication Technology*, vol. 16, pp. 529–540, August 1968.

[22] G. Franco, G.A.and Lachs, "An Orthogonal Coding Technique for Communications," in *IRE International Convension Record*, vol. 9, pp. 126–133, 1961.

[23] S. Darlington, "On digital single-sideband modulators," *IEEE Transactions on Circuit Theory*, vol. 17, pp. 409–414, Aug 1970.

[24] S. Weinstein and P. Ebert, "Data Transmission by Frequency-Division Multiplexing Using the Discrete Fourier Transform," *IEEE Transactions on Communication Technology*, vol. 19, pp. 628–634, October 1971.

[25] L. Cimini, "Analysis and Simulation of a Digital Mobile Channel Using Orthogonal Frequency Division Multiplexing," *IEEE Transactions on Communications*, vol. 33, pp. 665–675, Jul 1985.

[26] Y. Zhao and S.-G. Haggman, "Intercarrier interference self-cancellation scheme for OFDM mobile communication systems," *IEEE Transactions on Communications*, vol. 49, pp. 1185–1191, Jul 2001.

[27] T. Pollet, M. Van Bladel, and M. Moeneclaey, "BER sensitivity of OFDM systems to carrier frequency offset and Wiener phase noise," *IEEE Transactions on Communications*, vol. 43, pp. 191–193, Feb 1995.

[28] A. Wahab and M. Ain, "Clipping and time domain statistical method for papr reduction in ofdm system," in *9th International Conference on Environment and Electrical Engineering (EEEIC), 2010*, pp. 487–490, May 2010.

[29] R. van Nee, "OFDM codes for peak-to-average power reduction and error correction," in *Global Telecommunications Conference, 1996. GLOBECOM '96. 'Communications: The Key to Global Prosperity*, vol. 1, pp. 740–744 vol.1, Nov 1996.

[30] R. v. Nee and R. Prasad, *OFDM for Wireless Multimedia Communications.* Norwood, MA, USA: Artech House, Inc., 1st ed., 2000.

[31] P. Sharma, "Performance evaluation of OFDM system in terms of PAPR," in *Second International Conference on Advanced Computing Communication Technologies (ACCT), 2012*, pp. 214–218, Jan 2012.

[32] M. Sharif, M. Gharavi-Alkhansari, and B. Khalaj, "On the peak-to-average power of OFDM signals based on oversampling," *IEEE Transactions on Communications*, vol. 51, pp. 72–78, Jan 2003.

[33] C. Tellambura, "Computation of the continuous-time PAR of an OFDM signal with BPSK subcarriers," *IEEE Communications Letters*, vol. 5, pp. 185–187, May 2001.

[34] M. Sharif and B. Khalaj, "Peak to mean envelope power ratio of oversampled OFDM signals: an analytical approach," in *IEEE International Conference on Communications, 2001. ICC 2001.*, vol. 5, pp. 1476–1480 vol.5, 2001.

[35] D. Wulich, "Comments on the peak factor of sampled and continuous signals," *IEEE Communications Letters*, vol. 4, pp. 213–214, July 2000.

[36] S. Muller and J. Huber, "OFDM with reduced peak-to-average power ratio by optimum combination of partial transmit sequences," *Electronics Letters*, vol. 33, no. 5, pp. 368–369, 1997.

[37] T. Jiang and Y. Wu, "An Overview: Peak-to-Average Power Ratio Reduction Techniques for OFDM Signals," *IEEE Transactions on Broadcasting*, vol. 54, pp. 257–268, June 2008.

[38] Y. Rahmatallah and S. Mohan, "Peak-To-Average Power Ratio reduction in OFDM systems: A survey and taxonomy," *IEEE Communications Surveys Tutorials*, vol. 15, pp. 1567–1592, Fourth 2013.

[39] J. Urban and R. Marsalek, "OFDM PAPR reduction by Partial Transmit Sequences and Simplified Clipping with Bounded Distortion," in *18th International Conference Radioelektronika, 2008*, pp. 1–4, April 2008.

[40] Y. S. Cho, J. Kim, W. Y. Yang, and Chung G. Kang, *MIMO-OFDM wireless communications with MATLAB.* John Wiley & Sons, Inc., 2010.

[41] T. G. Pratt, N. Jones, L. Smee, and M. Torrey, "Ofdm link performance with companding for papr reduction in the presence of non-linear amplification," *IEEE Transactions on Broadcasting*, vol. 52, no. 2, pp. 261–267, 2006.

[42] D. Kim, D. Shi, Y. Park, and B. Song, "New peak-windowing for papr reduction of ofdm systems," in *Proc. Asia-Pacific Conference on Wearable Computing Systems (APWCS)*, pp. 169–173, 2005.

[43] K. R. Panta and J. Armstrong, "Effects of clipping on the error performance of ofdm in frequency selective fading channels," *IEEE Transactions on wireless communications*, vol. 3, no. 2, pp. 668–671, 2004.

[44] X. Wang, T. T. Tjhung, and C. Ng, "Reduction of peak-to-average power ratio of ofdm system using a companding technique," *IEEE transactions on broadcasting*, vol. 45, no. 3, pp. 303–307, 1999.

[45] M. J. Omidi, A. Minasian, H. Saeedi-Sourck, K. Kasiri, and I. Hosseini, "PAPR reduction in OFDM systems: Polynomial-based compressing and iterative expanding," *Wireless personal communications*, vol. 75, no. 1, pp. 103–118, 2014.

[46] B. Krongold and D. Jones, "Par reduction in ofdm via active constellation extension," *Broadcasting, IEEE Transactions on*, vol. 49, pp. 258–268, Sept 2003.

[47] J. Tellado and J. Cioffi, "Peak power reduction for multicarrier transmission," in *IEEE Global Communications Conference (GLOBECOM)*, 1998.

[48] S. H. Han, J. Cioffi, and J. H. Lee, "Tone injection with hexagonal constellation for peak-to-average power ratio reduction in OFDM," *Communications Letters, IEEE*, vol. 10, pp. 646–648, Sept 2006.

[49] T. Wattanasuwakull and W. Benjapolakul, "Papr reduction for ofdm transmission by using a method of tone reservation and tone injection," in *2005 5th International Conference on Information Communications & Signal Processing*, pp. 273–277, IEEE, 2005.

[50] G. Hill, M. Faulkner, and J. Singh, "Reducing the peak-to-average power ratio in ofdm by cyclically shifting partial transmit sequences," *Electronics Letters*, vol. 36, pp. 560–561, Mar 2000.

[51] G. W. P. Van Eetvelt and M. Tomlinson, “Peak to average power reduction forOFDM schemes by selective scrambling,” *Electronics Letters*, vol. 32, pp. 1963–1964(1), October 1996.

[52] P. Varahram, W. Al-Azzo, and B. Ali, “A low complexity partial transmit sequence scheme by use of dummy signals for PAPR reduction in OFDM systems,” *IEEE Transactions on Consumer Electronics*, vol. 56, pp. 2416–2420, November 2010.

[53] S. H. Muller, R. W. Bauml, R. E. H. Fischer, and J. B. Huber, “OFDM with reduced peak-to-average power ratio by multiple signal representation,” *In Annals of Telecommunications,*, vol. 52, pp. 58–67, 1997.

[54] S. Le Goff, S. Al-Samahi, B. K. Khoo, C. Tsimenidis, and B. Sharif, “Selected mapping without side information for PAPR reduction in OFDM,” *IEEE Transactions on Wireless Communications*, vol. 8, pp. 3320–3325, July 2009.

[55] M. Alard and R. Lassalle, “Principles of Modulation and Channel Coding for Digital braodcasting for Mobile Receivers,” *Europian Broadcasting Union Technical Review*, no. 224, pp. 3–25, 1987.

[56] L. Yang, R. Chen, K. Soo, and Y. Siu, “An efficient sphere decoding approach for PTS assisted PAPR reduction of OFDM signals,” *AEU - International Journal of Electronics and Communications*, vol. 61, pp. 684–688, Nov. 2007.

[57] R. Saxena and H. D. Joshi, “Ofdm and its major concerns: A study with way out,” *IETE Journal of Education*, vol. 54, no. 1, pp. 26–49, 2013.

[58] A. Jayalath and C. Tellambura, “Reducing the peak-to-average power ratio of orthogonal frequency division multiplexing signal through bit or symbol interleaving,” *Electronics Letters*, vol. 36, pp. 1161–1163, Jun 2000.

[59] Y. Wang, W. Chen, and C. Tellambura, "PAPR reduction method based on parametric minimum cross entropy for OFDM signals," *IEEE Communications Letters*, vol. 14, pp. 563–565, June 2010.

[60] S. G. Kang, S. Member, and J. G. Kim, "A Novel Subblock Partition Scheme for Partial Transmit Sequence OFDM," *IEEE Transactions on Broadcasting*, vol. 45, no. 3, p. 333, 1999.

[61] C. Tellambura, "Improved phase factor computation for the PAR reduction of an OFDM signal using PTS," *IEEE Communications Letters*, vol. 5, pp. 135–137, Apr. 2001.

[62] S. H. Han and J. H. Lee, "Papr reduction of OFDM signals using a reduced complexity PTS technique," *IEEE Signal Processing Letters*, vol. 11, pp. 887–890, Nov 2004.

[63] T. Jiang, W. Xiang, P. Richardson, J. Guo, and G. Zhu, "PAPR Reduction of OFDM Signals Using Partial Transmit Sequences With Low Computational Complexity," *IEEE Transactions on Broadcasting*, vol. 53, pp. 719–724, Sept 2007.

[64] S.-J. Ku, C.-L. Wang, and C.-H. Chen, "A Reduced-Complexity PTS-Based PAPR Reduction Scheme for OFDM Systems," *IEEE Transactions on Wireless Communications*, vol. 9, pp. 2455–2460, August 2010.

[65] J.-C. Chen, "Partial transmit sequences for PAPR reduction of OFDM signals with stochastic optimization techniques," *IEEE Transactions on Consumer Electronics*, vol. 56, pp. 1229–1234, Aug 2010.

[66] X. S. Yang, "Firefly algorithms for multimodal optimization," vol. 5792 of *Lecture Notes in Computer Science*, pp. 169–178, Springer Berlin Heidelberg, 2009.

[67] X. S. Yang and S. Deb, "Cuckoo Search via Levy flights," in *World Congress on Nature Biologically Inspired Computing, NaBIC 2009.*, pp. 210–214, Dec 2009.

[68] H. Nikookar and K. Lidsheim, "Random phase updating algorithm for OFDM transmission with low PAPR," *IEEE Transactions on Broadcasting*, vol. 48, pp. 123–128, Jun 2002.

[69] H. Yoo, F. Guilloud, and R. Pyndiah, "PAPR reduction for LDPC coded OFDM systems using binary masks and optimal LLR estimation," *Signal Processing*, vol. 91, no. 11, pp. 2606 – 2614, 2011.

[70] A. Alavi, C. Tellambura, and I. Fair, "PAPR reduction of OFDM signals using partial transmit sequence: an optimal approach using sphere decoding," *IEEE Communications Letters*, vol. 9, pp. 982–984, Nov 2005.

[71] J.-C. Chen, "Partial Transmit Sequences for Peak-to-Average Power Ratio Reduction of OFDM Signals With the Cross-Entropy Method," *IEEE Signal Processing Letters*, vol. 16, pp. 545–548, June 2009.

[72] S.-J. Ku, C.-L. Wang, and C.-H. Chen, "A Reduced-Complexity PTS-Based PAPR Reduction Scheme for OFDM Systems," *IEEE Transactions on Wireless Communications*, vol. 9, pp. 2455–2460, August 2010.

[73] J.-C. Chen, "Application of Quantum-Inspired Evolutionary Algorithm to Reduce PAPR of an OFDM Signal Using Partial Transmit Sequences Tech-

nique," *IEEE Transactions on Broadcasting*, vol. 56, pp. 110–113, March 2010.

[74] J. Hou, J. Ge, and J. Li, "Peak-to-Average Power Ratio Reduction of OFDM Signals Using PTS Scheme With Low Computational Complexity," *IEEE Transactions on Broadcasting*, vol. 57, pp. 143–148, March 2011.

[75] L. Wang and J. Liu, "PAPR Reduction of OFDM Signals by PTS With Grouping and Recursive Phase Weighting Methods," *IEEE Transactions on Broadcasting*, vol. 57, pp. 299–306, June 2011.

[76] P. Varahram and B. Ali, "Partial transmit sequence scheme with new phase sequence for PAPR reduction in OFDM systems," *IEEE Transactions on Consumer Electronics*, vol. 57, pp. 366–371, May 2011.

[77] X. Y. S. L. Z. Zhu and T. Zhang, "An improved artificial bee colony-partial transmit sequence algorithm for PAPR reduction in OFDM systems," *Int. J. of Wireless and Mobile Computing*, vol. 6, pp. 473–480, Jan 2013.

[78] C.-E. Weng, C.-W. Chang, C.-H. Chen, and H.-L. Hung, "Novel Low-Complexity Partial Transmit Sequences Scheme for PAPR Reduction in OFDM Systems Using Adaptive Differential Evolution Algorithm," *Wireless Personal Communications*, vol. 71, no. 1, pp. 679–694, 2013.

[79] L. Li, D. Qu, and T. Jiang, "Partition Optimization in LDPC-Coded OFDM Systems With PTS PAPR Reduction," *IEEE Transactions on Vehicular Technology*, vol. 63, pp. 4108–4113, Oct 2014.

[80] W. Xiao, H. Deng, F. Jiang, K. Zhu, and L. Yin, "Peak-to-average power ratio reduction in orthogonal frequency division multiplexing visible light

communications system using a combination of a genetic algorithm and a hill-climbing algorithm," *Optical Engineering*, vol. 54, no. 3, p. 036106, 2015.

[81] L. Cimini and N. Sollenberger, "Peak-to-average power ratio reduction of an OFDM signal using partial transmit sequences with embedded side information," in *Global Telecommunications Conference, 2000. GLOBECOM '00. IEEE*, vol. 2, pp. 746–750 vol.2, 2000.

[82] A. Jayalath and C. Tellambura, "Side information in PAR reduced PTS-OFDM signals," in *14th IEEE Proceedings on Personal Indoor and Mobile Radio Communications, PIMRC 2003.*, vol. 1, pp. 226–230 Vol.1, Sept 2003.

[83] S.-A. Kim and H.-G. Ryu, "Design and Analysis of Side Information Embedded PTS Scheme in the OFDM Communication System," in *Wireless Algorithms, Systems, and Applications* (X. Cheng, W. Li, and T. Znati, eds.), vol. 4138 of *Lecture Notes in Computer Science*, pp. 550–560, Springer Berlin Heidelberg, 2006.

[84] L. Yang, K. Soo, S. Li, and Y. Siu, "PAPR Reduction Using Low Complexity PTS to Construct of OFDM Signals Without Side Information," *IEEE Transactions on Broadcasting*, vol. 57, pp. 284–290, June 2011.

[85] H. Chen and H. Liang, "PAPR Reduction of OFDM Signals Using Partial Transmit Sequences and Reed-Muller Codes," *IEEE Communications Letters*, vol. 11, pp. 528–530, June 2007.

[86] A. Ghassemi and T. Gulliver, "PAPR reduction of OFDM using PTS and error-correcting code subblocking," *IEEE Transactions on Wireless Communications*, vol. 9, pp. 980–989, March 2010.

[87] X.-S. Yang, *Nature-Inspired Metaheuristic Algorithms.* Luniver Press, 2008.

[88] M.-H. Horng, "Vector quantization using the firefly algorithm for image compression," *Expert Systems with Applications*, vol. 39, no. 1, pp. 1078–1091, 2012.

[89] A. H. Gandomi, X.-S. Yang, and A. H. Alavi, "Mixed variable structural optimization using firefly algorithm," *Computers & Structures*, vol. 89, no. 23, pp. 2325–2336, 2011.

[90] J. Senthilnath, S. Omkar, and V. Mani, "Clustering using firefly algorithm: performance study," *Swarm and Evolutionary Computation*, vol. 1, no. 3, pp. 164–171, 2011.

[91] X. S. Yang, "Firefly algorithm, stochastic test functions and design optimisation," *Int. J. Bio-Inspired Comput.*, vol. 2, pp. 78–84, Mar. 2010.

[92] C. O'Toole, *Firefly Encyclopedia of Insects and Spiders*. Firefly Books, 2002.

[93] X.-S. Yang, *Firefly Algorithm, Lévy Flights and Global Optimization*, pp. 209–218. London: Springer London, 2010.

[94] X. S. Yang, *Engineering Optimization: An Introduction with Metaheuristic Applications*. John Wiley & Sons, Inc., 2010.

[95] I. Fister, I. F. Jr., X.-S. Yang, and J. Brest, "A comprehensive review of firefly algorithms," *Swarm and Evolutionary Computation*, vol. 13, no. 0, pp. 34 – 46, 2013.

[96] X.-S. Yang and S. Deb, "Engineering optimisation by cuckoo search," *International Journal of Mathematical Modelling and Numerical Optimisation*, vol. 1, no. 4, pp. 330–343, 2010.

[97] X. S. Yang, "Firefly algorithm : Recent Advances and Applications," *International Journal of Swarm Intelligence*, vol. 1, no. 1, pp. 36–50, 2013.

[98] X.-S. Yang and S. Deb, "Multiobjective cuckoo search for design optimization," *Computers & Operations Research*, vol. 40, no. 6, pp. 1616–1624, 2013.

[99] P. Civicioglu and E. Besdok, "A conceptual comparison of the cuckoo-search, particle swarm optimization, differential evolution and artificial bee colony algorithms," *Artificial Intelligence Review*, vol. 39, no. 4, pp. 315–346, 2013.

[100] X.-S. Yang and S. Deb, "Cuckoo search: recent advances and applications," *Neural Computing and Applications*, vol. 24, no. 1, pp. 169–174, 2014.

[101] A. R. Yildiz, "Cuckoo search algorithm for the selection of optimal machining parameters in milling operations," *The International Journal of Advanced Manufacturing Technology*, vol. 64, no. 1-4, pp. 55–61, 2013.

[102] A. H. Gandomi, X.-S. Yang, and A. H. Alavi, "Cuckoo search algorithm: a metaheuristic approach to solve structural optimization problems," *Engineering with computers*, vol. 29, no. 1, pp. 17–35, 2013.

[103] X.-S. Yang, "Cuckoo search and firefly algorithm," *Studies in computational intelligence. Switzerland: Springer*, vol. 516, 2014.

[104] M. Mahdavi, M. Fesanghary, and E. Damangir, "An improved harmony search algorithm for solving optimization problems," *Applied Mathematics and Computation*, vol. 188, pp. 1567–1579, May 2007.

[105] J. Gao, J. Wang, B. Wang, and X. Song, "A Papr Reduction Algorithm Based on Harmony Research for OFDM Systems," *Procedia Engineering*, vol. 15, pp. 2665–2669, Jan. 2011.

[106] Z. W. Geem;, J. H. Kim;, and L. G.V., “A new heuristic optimization algorithm: Harmony search,” *SIMULATION*, vol. 76, no. 2, pp. 60–68, 2001.

[107] Z. W. Geem, *Music-Inspired Harmony Search Algorithm: Theory and Applications*. Springer Publishing Company, Incorporated, 1st ed., 2009.

[108] E. M. Kermani, H. Salehinejad, and S. Talebi, “PAPR reduction of OFDM signals using harmony search algorithm,” *18th International Conference on Telecommunications, 2011*, pp. 90–94, May 2011.

[109] D. Manjarres, I. Landa-Torres, S. Gil-Lopez, J. D. Ser, M. Bilbao, S. Salcedo-Sanz, and Z. Geem, “A survey on applications of the harmony search algorithm,” *Engineering Applications of Artificial Intelligence*, vol. 26, no. 8, pp. 1818 – 1831, 2013.

[110] X.-S. Yang, “Harmony search as a metaheuristic algorithm,” in *Music-Inspired Harmony Search Algorithm* (Z. Geem, ed.), vol. 191 of *Studies in Computational Intelligence*, pp. 1–14, Springer Berlin Heidelberg, 2009.

[111] P. Yadav, R. Kumar, S. Panda, and C. Chang, “An intelligent tuned harmony search algorithm for optimisation,” *Information Sciences*, vol. 196, no. 0, pp. 47 – 72, 2012.

[112] O. M. Alia and R. Mandava, “The variants of the harmony search algorithm: an overview,” *Artificial Intelligence Review*, vol. 36, pp. 49–68, Jan. 2011.

[113] M. A. Al-Betar, I. A. Doush, A. T. Khader, and M. A. Awadallah, “Novel selection schemes for harmony search,” *Applied Mathematics and Computation*, vol. 218, no. 10, pp. 6095 – 6117, 2012.

Disseminations

Journal Papers

1. **Mangal Singh** and Sarat Kumar Patra, "Partial Transmit Sequence Based Cuckoo Search Optimization for Peak-to-Average Power Ratio Reduction in Orthogonal Frequency Division Multiplexing Systems", *Journal of Computational Intelligence and Electronic Systems, Volume 5, Number 1, March 2016, pp. 28-34(7)*

2. **Mangal Singh** and Sarat Kumar Patra, "On the PTS optimization using firefly algorithm for PAPR reduction in OFDM systems", *IETE Technical Review, (Under review Manuscript ID: TITR-2016-0759), Second review submitted with minor revision on 23.04.17*

3. **Mangal Singh** and Sarat Kumar Patra, "Partial Transmit Sequence (PTS) optimization using improved harmony search algorithm for PAPR reduction in OFDM", *ETRI Journal, (Under review Manuscript ID: RP1612-0919), First review submitted with minor revision on 04.07.17*

4. **Mangal Singh** and Sarat Kumar Patra, "Investigations on evolutionary algorithms for PAPR performance analysis using PTS in OFDM systems", *IETE Journal of Research* (To be communicated)

Conference Papers

1. **Mangal Singh** and Sarat Kumar Patra, "Analysis of PAPR Reduction Schemes in LTE-OFDM System" *IEEE International Conference on Advanced Research in Engineering and Technology (ICARET-2013), K L University, Vaddeswaram, Andhra Pradesh, India, Feb. 2013.*

2. **Mangal Singh** and Sarat Kumar Patra, "Partial Transmit Sequence (PTS) based PAPR reduction for OFDM using improved harmony search evolutionary algorithm ", *8th International Conference on Bio-inspired Information and Communications Technologies (BICT-2014), Boston, MA, USA, Dec 2014.*

3. **Mangal Singh** and Sarat Kumar Patra, "On the performance analysis of Partial Transmit Sequence using modified flipping algorithm for PAPR reduction in OFDM systems", *IEEE International Conference on Computer, Communication, Control and Information Technology, (C3IT-2015), Hooghly, West Bengal, India, Feb. 2015.*

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Publications

- 1 Journal Articles (Published)
- 1 Journal Articles (First review submitted on 12.11.2016)
- 2 Journal Articles (Communicated)
- 3 Conference (Published)